

UC Berkeley

UC Berkeley Previously Published Works

Title

Multi-locus genomic signatures of local adaptation to snow across the landscape in California populations of a willow leaf beetle

Permalink

<https://escholarship.org/uc/item/8dq3568k>

Journal

Proceedings of the Royal Society B, 290(2005)

ISSN

0962-8452

Authors

Keller, Abigail G
Dahlhoff, Elizabeth P
Bracewell, Ryan
[et al.](#)

Publication Date

2023-08-30

DOI

10.1098/rspb.2023.0630

Supplemental Material

<https://escholarship.org/uc/item/8dq3568k#supplemental>

Copyright Information

This work is made available under the terms of a Creative Commons Attribution License, available at <https://creativecommons.org/licenses/by/4.0/>

Peer reviewed

1 **Multi-locus genomic signatures of local adaptation to snow across the landscape in**
2 **California populations of a willow leaf beetle**

3

4 **Authors:** Abigail G. Keller¹, Elizabeth P. Dahlhoff², Ryan Bracewell³, Kamalakar Chatla¹, Doris
5 Bachtrog¹, Nathan E. Rank⁴, Caroline M. Williams¹

6

7 ¹Department of Integrative Biology, University of California, Berkeley, California, USA

8 ²Department of Biology, Santa Clara University, Santa Clara, California, USA

9 ³Department of Biology, Indiana University Bloomington, Bloomington, Indiana, USA

10 ⁴Department of Biology, Sonoma State University, Rohnert Park, California, USA

11

12 **Corresponding Author:**

13 Abigail G. Keller, Department of Integrative Biology, University of California, Berkeley,

14 California, USA; email: agkeller@berkeley.edu

15

16 **Keywords:** Climate change, cold tolerance, insect, local adaptation, landscape genomics, winter

17 **Abstract**

18 Organisms living in mountains contend with extreme climatic conditions, including short
19 growing seasons and long winters with extensive snow cover. Anthropogenic climate change is
20 driving unprecedented, rapid warming of montane regions across the globe, resulting in reduced
21 winter snowpack. Loss of snow as a thermal buffer may have serious consequences for animals
22 overwintering in soil, yet little is known about how variability in snowpack acts as a selective
23 agent in montane ecosystems. Here we examine genomic variation in California populations of
24 the leaf beetle *Chrysomela aeneicollis*, an emerging natural model system for understanding how
25 organisms respond to climate change. We used a genotype-environment association approach to
26 identify genomic signatures of local adaptation to microclimate in populations from three
27 montane regions with variable snowpack and a coastal region with no snow. We found that both
28 winter-associated environmental variation and geographic distance contribute to overall genomic
29 variation across the landscape. We identified non-synonymous variation in novel candidate loci
30 associated with cytoskeletal function, ion transport and membrane stability, cellular processes
31 associated with cold tolerance in other insects. These findings provide intriguing evidence that
32 variation in snowpack imposes selective gradients in montane ecosystems.

33 **Introduction**

34 Seasonality serves as one of the strongest and most ubiquitous sources of environmental
35 variation impacting natural systems, with distinct selective forces operating between periods of
36 summer growth and reproduction and overwintering survival (Fretwell, 1972; Williams et al.,
37 2017). For small montane ectotherms, elevated and variable air temperatures during summertime
38 can cause physiological stress during critical periods of reproduction, growth, and development
39 (Dahlhoff et al., 2008; McMillan et al., 2005; Nearing et al. 2003). As hotter, drier summers
40 become more common, upslope shifts in montane insect species are becoming more frequent,
41 posing novel challenges at the limits of physiological tolerance (Larsen, 2012; Moret et al.,
42 2016). For organisms that overwinter beneath the soil, snow cover is a key environmental factor
43 influencing physiology and survival because snow buffers microclimate variability (Pauli et al.,
44 2013; Slatyer et al., 2022; Zhu et al., 2019). Climate change is causing more prevalent, intense,
45 and lengthy droughts, which in turn leads to more winters with a higher elevation snowline and
46 lower total snowpack (Huning & AghaKouchak, 2020; Mote et al., 2018). Reductions in
47 snowpack may expose organisms overwintering in the soil to temperature extremes that cause
48 physiological stress, reducing their overwintering survival and reproductive success at
49 subsequent summer emergence. Recent declines in insect populations in montane environments
50 documented across the globe demonstrate the urgency in gaining a clear understanding of how
51 organisms cope with greater seasonal variability in temperature and precipitation in montane
52 ecosystems (Birrell et al., 2020; Halsch et al., 2021; Shah et al., 2020). Seasonal fluctuation can
53 maintain genetic polymorphisms within populations (Haldane & Jayakar, 1963; Wittmann et al.,
54 2017), and variation in the extent and magnitude of seasonal fluctuations can generate spatial

55 clines in allelic variants (Conover, 1992; Rank & Dahlhoff, 2002; Rhomberg & Singh, 1986).
56 Elucidating how past climatic conditions have structured genetic variation and corresponding
57 physiological responses for organisms in these habitats will be critical for predicting their
58 responses to future environmental change.

59 Local adaptation, which occurs when resident genotypes have a higher relative fitness in
60 their local habitat than genotypes originating from other habitats, is an important mechanism by
61 which genetic variation is maintained in heterogeneous environments (Felsenstein, 1976;
62 Hedrick et al., 1976; Kawecki & Ebert, 2004). The extent and persistence of local adaptation is
63 determined by a balance between natural selection for alleles that confer improved reproductive
64 success in a particular microclimate and the homogenizing effects of gene flow and other neutral
65 processes (Forester et al., 2016; Kawecki & Ebert, 2004; Nadeau et al., 2016; Orsini et al., 2013;
66 Slatkin, 1987). Neutral processes that influence patterns of genetic variation among populations
67 include dispersal rates, colonization history, and population expansion and contraction, which in
68 turn affects levels of genetic drift (Nadeau et al., 2016; Orsini et al., 2013). Local adaptation may
69 be detected by identifying a stronger genetic variant ‘signal’ from weaker, non-selective ‘noise’
70 (Shafer & Wolf, 2013; Wang & Bradburd, 2014). Unfortunately, selective climatic gradients,
71 geography, and migration corridors tend to covary, which complicates quantifying the relative
72 contribution of selective and neutral evolutionary forces; thus, effects of isolation by distance and
73 population structure must be taken into account before patterns of genomic variation can be
74 associated with selective features of the environment (Forester et al., 2018a; Frichot et al., 2013;
75 Rellstab et al., 2015; Sork et al., 2013).

76 In this study, we investigated relationships between microclimatic factors and genetic
77 variation in the willow leaf beetle *Chrysomela aeneicollis*, a well-described model species for
78 understanding how climate change impacts montane ecosystems (Dahlhoff et al., 2019; Millstein,
79 2006; Rank & Dahlhoff, 2002). This insect is ideal for investigating processes of local adaptation
80 in a region of high topographic and seasonal landscape heterogeneity (Camus, 2020). During the
81 brief summer growing season, this univoltine beetle species mates, lays eggs, and undergoes one
82 generation of larval development before new adults emerge and feed before winter returns
83 (Smiley & Rank, 1986). They overwinter in the soil as freeze-tolerant adults for eight to nine
84 months before emergence of reproductively mature adults (Boychuck et al., 2015; Roberts et al.,
85 2021).

86 In western North America, *C. aeneicollis* is found living on willows in cool, moist
87 habitats separated by regions of arid or Mediterranean climates, resulting in highly fragmented
88 distribution with little connectivity among populations (Brown, 1956; Dellicour et al., 2014). In
89 California, this species inhabits regions with distinct microclimate and seasonal characteristics:
90 along high-elevation (2700 - 3400 m) streams and bogs in the Sierra Nevada, in isolated montane
91 populations on the edge of the Great Basin, and in low elevation riparian habitats along the
92 Northern California coast. Within the Sierra Nevada, populations experience stressfully warm
93 and cold temperatures throughout the year and their distribution is affected by seasonality and
94 elevation, with populations contracting upslope and declining in abundance during droughts and
95 growing in size and expanding to lower elevations after wet, snowy winters (Dahlhoff et al.,
96 2019; McMillan et al., 2005; Rank, 1994; Rank et al., 2020; Roberts et al., 2021; Smiley &
97 Rank, 1986). Despite these fluctuations in population size, Sierra Nevada populations have

98 maintained high levels of heterozygosity at protein coding genes and other loci and show no
99 deviation from Hardy Weinberg expectations with respect to expected versus observed genotype
100 frequencies (Rank 1992a, Rank et al. 2020), suggesting that they are sufficiently large to avoid
101 bottlenecks and effects of inbreeding. Montane populations show evidence of substantial, stable
102 genetic differentiation along a 60 km latitudinal gradient, from the South Fork of the Kings River
103 in the south to Rock Creek in the north, with especially high divergence at mitochondrial loci
104 and the metabolic enzyme locus *phosphoglucose isomerase*, *Pgi* (Dahlhoff et al., 2008; Rank,
105 1992a; Rank et al., 2020; Rank & Dahlhoff, 2002). Prior laboratory and field studies have also
106 shown that effects of temperature on performance and fitness components vary among
107 individuals with different nuclear and mitochondrial variants (Camus, 2020; Dahlhoff et al.,
108 2019; Dahlhoff & Rank, 2000; Dick et al., 2013; Rank et al., 2020). While extensive studies
109 support the hypothesis that variation at metabolic loci such as *Pgi* and the mitochondrion reflect
110 local adaptation (Bracewell et al., 2023; Dahlhoff et al., 2008; Dahlhoff & Rank, 2000; Rank &
111 Dahlhoff, 2002), we lack information about how variation throughout the genome reflects the
112 complex interaction of neutral and adaptive processes across the beetle's range.

113 Here, we address this gap by evaluating relationships between genomic variation and
114 environmental conditions in locations where willow beetle populations occur in four distinct
115 ecoregions of California (Griffith et al., 2016). We quantified differentiation at nuclear loci
116 among populations in three montane regions in Eastern California and populations in an isolated
117 coastal area; this sampling design covers all known regions within California where this species
118 is currently known to occur (Brown, 1956; Dellicour et al., 2014). We identified selective
119 microclimatic gradients that contribute to spatial patterns of potentially adaptive genomic

120 variation across the landscape, then used this information to predict functions of newly identified
121 genes that vary along microclimatic gradients to examine how genomic differentiation among
122 these regions may contribute to local adaptation.

123

124 **Results**

125 *Sequencing and marker filtering*

126 Illumina sequencing generated 5.06 billion paired-end reads from 175 individuals in 12
127 populations (Table 1), of which 4.05 billion total reads (80.1%) passed initial quality filters (per
128 sample: mean = 23.1 million, sd = 7.9 million). The joint genotype calling workflow identified
129 12 million hard-filtered biallelic SNPs (Tables S1, S2). We then used a conservative SNP
130 filtering approach based on minor allele frequency (MAF), heterozygosity, and inbreeding
131 coefficient, resulting in 22,323 SNPs across all individuals and 12 populations. Filtering
132 thresholds that contributed substantially to the reduced set of analyzed SNPs were those that
133 removed SNPs with a MAF < 0.01 (Table S2B) and that removed loci with low quality reads
134 within populations (Table S2C). These SNPs were distributed evenly across the nuclear genome
135 (Table S1).

136 *Microclimate simulation*

137 The NicheMapR microclimate model simulated 24 variables for the 12 beetle populations that
138 represent air, soil, and snow conditions beetles experience throughout their lifecycle (Table S3).
139 Simulated environmental variables demonstrated high sensitivity to the shade input parameter in
140 the model (Fig S1), but relative multivariate environmental distances between populations were
141 consistent between minimum and maximum shade conditions (Fig S2). Simulated microclimatic
142 data under minimum shade conditions were more concordant with available empirical
143 measurement based on RMSE (Table S4), so downstream analyses were therefore conducted
144 using simulated environmental variables under 10% shade.

145 *Population genomic differentiation across California landscape*

146 The first two principal components on population-level minor allele frequencies explained 55.8%
147 of total genomic variation (Fig 1B). Eastern Cascade and Coast Range ecoregions exhibited the
148 greatest genomic divergence among populations, and population genomic variation in the Sierra
149 Nevada and Central Basin ecoregions followed a latitudinal gradient (Fig 1; Table S5). SNP
150 filtering thresholds used in analyses did not meaningfully influence estimates of population
151 structure compared to more relaxed filter thresholds (Fig S3-S5).

152 A population genetic structure analysis was used to estimate proportions of individual
153 genomes originating from ancestral gene pools based on the five populations determined by
154 selecting a value of K that minimized cross entropy (Fig S6). Individuals in the Sierra Nevada
155 ecoregion show a strong pattern of genetic differentiation with latitude (Fig 1). Based on
156 proportions of estimated ancestral coefficients, individuals in the southern drainage Tuttle Creek
157 (TC) are genetically distinct and belong to one ancestral population. Individuals in Taboose Pass
158 (TP) are mixed, sharing ancestry with neighbors in Tuttle Creek to the south, Big Pine (BP) and
159 Baker (BK) Creek to the north. Individuals in South Bishop Creek (BC) and Tye Lakes (TL)
160 share ancestry with both southern (BP, BK) and northern (NF, PC, RC) populations, which in
161 turn share ancestry with those from the Great Basin (DC). Individuals collected in Eastern
162 Cascades and Coast Range ecoregions were genetically distinct from each other and from the
163 Sierra Nevada-Great Basin complex (Fig 1).

164 Analysis of pairwise F_{st} values among population pairs revealed that populations in the
165 montane Eastern Cascades region were more similar to montane populations in the Sierra
166 Nevada and Great Basin than they were to Coast Range populations, despite similar geographic

167 distances separating each region (Fig 2). When populations were classified by habitat type
168 (coastal or mountain), F_{st} values for “coast vs. mountain” population pairs were four-fold greater
169 (LSM = 0.43 ± 0.02) than those for “mountain vs. mountain” population pairs (LSM = $0.11 \pm$
170 0.01 , $F_{1,63} = 197.4$, $P < 0.001$; Fig 2). The overall relationship between geographic distance and
171 F_{st} was similar within the two types of population pairs and was consistent with ‘isolation by
172 distance’ genetic differentiation ($F_{1,63} = 24.5$, $P < 0.001$; Fig 2). Together, these results suggest
173 that isolation by distance and isolation by environment (coastal versus montane) both shape
174 genomic differentiation, and differences in environmental conditions appear to strongly influence
175 genetic composition of *C. aeneicollis* populations.

176 *Associations between environmental and genomic variation*

177 *Partial redundancy analysis (pRDA)*- The pRDA made it possible to identify specific genetic
178 polymorphisms that were associated with environmental differences among populations. Among
179 all California populations, the pRDA was globally significant ($F_{2,7} = 2.18$, $P = 0.001$; Fig 3), and
180 the constraining environmental matrix explained 17.1% of variation in genomic data, while the
181 conditioning spatial matrix explained 19.0% of genomic variation. The forward selection
182 procedure identified a significant positive spatial variable (MEM1), which was retained as
183 conditioning variable in pRDA. The forward selection procedure identified annual air
184 temperature range at 1.75 m above ground level (annual $T_{max} - T_{min}$) and maximum daily snowfall
185 as significant environmental predictors of genomic variation (Fig 3; annual air temperature range
186 $F_{1,7} = 2.28$, $P = 0.001$; maximum daily snowfall $F_{1,7} = 2.08$, $P = 0.001$). The first and second
187 RDA axes also explained substantial proportions of genomic variation (RDA1 = 18.7%, $F_{1,7} =$
188 2.32 , $P = 0.014$; RDA2 = 16.6% $F_{1,7} = 2.05$, $P = 0.022$). Candidate single nucleotide

189 polymorphisms (SNPs) were identified based on high correlation with temperature- and snow-
190 related environmental variables ($r > |0.65|$) and z-score values of loadings of loci in ordination
191 space (z scores ± 2.1 , two-tailed $P = 0.036$). Based on these criteria, 107 SNPs were identified as
192 candidate loci (Fig 3). Sixty-eight SNPs were related to annual air temperature range, thirty-
193 seven to maximum daily snowfall, and two were related to both temperature and snowfall (Table
194 S6). When the coastal Gualala River population was excluded, the pRDA was globally
195 significant ($F_{1,8} = 2.04$, $P = 0.021$; Fig S7), and with MEM1 as the conditioning variable, the
196 forward selection procedure identified only maximum daily snowfall as a significant predictor of
197 genomic variation. Using the above candidate loci criteria, 116 SNPs were related to maximum
198 snowfall (Table S9).

199 *Latent factor mixed model (LFMM)*- The LFMM represents a second approach to identify SNPs
200 related to environmental variability while accounting for overall population genetic structure.
201 With all California populations, a LFMM was run with five estimated ancestry coefficients as
202 latent factors to test single-locus relationships with annual air temperature range and maximum
203 daily snowfall (ancestry coefficients shown in Fig 1). A large proportion of identified
204 polymorphisms (19.2%; 4,289 SNPs) were associated with annual air temperature range, and
205 7.2% (1,603 SNPs) were associated with maximum daily snowfall (Fig 4). Using the LFMM
206 excluding the coastal Gualala River population and four ancestral populations, 1,471 SNPs
207 (6.6% total) were associated with maximum snowfall (Table S9, Fig S8).

208 *SNP and protein functional annotations*

209 To reduce probability of false positive associations and narrow the search for candidate
210 polymorphisms, we focused on SNPs identified by both pRDA and LFMM, and we assessed

211 associations across coastal and montane populations and then again using only montane
212 populations (Tables 2, S6, S9). In analyses with all populations, most SNPs correlated with
213 annual air temperature range in pRDA were also identified using LFMM (67 of 70). A slightly
214 lower proportion of SNPs associated with maximum daily snowfall based on pRDA were also
215 identified by LFMM (26 of 39; Table S6). In analyses with only montane populations, most
216 SNPs correlated with maximum daily snowfall based on pRDA were also identified by LFMM
217 (79 of 116), and 18 SNPs identified in the pRDA with only montane populations were also
218 identified in analyses with coastal and montane populations (Table S9).

219 Analyses of all populations and only montane populations identified three non-
220 synonymous SNPs associated with maximum daily snowfall found in genes coding for proteins
221 involved in cell structure and movement (inverted formin-2 and microtubule-actin cross-linking
222 factor). Analyses including all populations or only montane populations identified five non-
223 synonymous SNPs associated daily snowfall that are found in genes coding for proteins involved
224 in ion transport or cellular membrane activity (Table 3, S8A, S11A). Three non-synonymous
225 SNPs associated with air temperature range across all populations were found in genes coding
226 for proteins involved in intracellular signaling and energetics [cytochrome p450, phospholipid
227 transfer protein, (Table 3)].

228

229 **Discussion**

230 Detecting accurate signals of local adaptation in the genome requires linking observed genetic
231 patterns to underlying selective features of the environment while accounting for associations
232 imposed by neutral processes. Here we demonstrate that populations of the willow leaf beetle
233 *Chrysomela aeneicollis* across California are differentiated across the nuclear genome, and we
234 provide strong evidence that snow serves as a prominent selective gradient and driver of local
235 adaptation across their geographic range. We show that both large-scale variation in snowfall
236 across the California landscape and small-scale variation in snowfall within montane locations
237 are associated with adaptive genetic variation. Specifically, we provide evidence that variation in
238 maximum daily snowfall is linked to non-synonymous polymorphisms in genes associated with
239 cytoskeletal motility, ion transport, and membrane structure and function, highlighting the
240 potential role of adaptive protein modifications that could enhance insect cold tolerance in cold
241 snowy regions.

242 *Spatial patterns of genetic divergence in Chrysomela aeneicollis*

243 Results of this study reveal that populations of the willow leaf beetle *Chrysomela aeneicollis*
244 living in different regions of California are genetically differentiated across loci in the nuclear
245 genome. Three of four ecoregions sampled show substantial levels of genetic divergence among
246 them, such that North Coast populations are distinct from those in the Eastern Cascades
247 ecoregion, and both of those populations are distinct from populations in the Sierra Nevada and
248 Great Basin (Fig 1). Within Eastern California, populations from northern drainages of the
249 Eastern Sierra Nevada are less genetically isolated from populations sampled in the neighboring
250 White Mountains than those found in southern drainages of the Sierra Nevada. Furthermore,

251 consistent with previous studies, populations within the Sierra Nevada show relatively high
252 levels of genetic divergence given their relatively close geographic proximity (Fig 1) (Dahlhoff
253 et al., 2008; Rank, 1992a; Rank et al., 2020). Patterns of genetic differentiation separating
254 populations in different ecoregions suggest that geographic and seasonal environmental variation
255 present a major selective pressure on alleles in the nuclear genome and that genes related to
256 thriving under different local environmental conditions contribute to local adaptation among
257 populations of *C. aeneicollis* (Fig 2).

258 The strong pattern of geographic differentiation of genomic variation across California
259 was illustrated for the first time in the present study, but it is consistent with findings of Dellicour
260 et al. (2014). The earlier study found that *C. aeneicollis* populations in Western North America
261 (Montana, coastal Oregon, Colorado, and California) were strongly differentiated at
262 mitochondrial and nuclear genetic markers, suggesting that geographic isolation among these
263 regions predates recent fluctuations in the extent of glaciation over the past 50,000 years.
264 Isolation of populations at mitochondrial loci was greater than nuclear genes, but there was
265 overall agreement among loci that differentiation among geographic regions was substantial,
266 which would contribute to conditions favoring local adaptation (Dellicour et al., 2014). To date,
267 this study provides the best picture of signatures of adaptation to seasonal variation in this wide-
268 ranging insect.

269 *Maximum daily snowfall variation contributes to adaptive genetic variation*

270 Identifying climatic variables that act as drivers of spatially varying selection will be critical for
271 predicting evolutionary responses to climate change and environmental disturbance (Bay et al.,
272 2018). Among all simulated microclimate conditions that represent air, soil, and snow conditions

273 throughout the year, we found that maximum daily snowfall explains a significant portion of
274 variation in genomic data, after controlling for spatial autocorrelation and population history (Fig
275 3, Fig S7). This association is identified both across the California landscape, where climatic
276 conditions differ greatly between coastal and montane populations, as well as within montane
277 populations, where differences in climatic conditions are more subtle. Comparisons made within
278 montane populations suggest that this snowfall gradient may characterize spatially varying
279 selective pressures related to winter cold exposure within mountain ecoregions (Fig S9). Eco-
280 physiological models for *C. aeneicollis* indicate that the relationship between elevation and cold
281 exposure in soil is strongly non-linear, with cold exposure peaking at mid-elevation montane
282 populations that are not buffered by persistent snow cover (Roberts et al., 2021). Since snow
283 decouples the relationship between air and soil temperatures, variation in snow cover reflects
284 variation in cold exposure in the soil at a given elevation. Without the thermal buffer that snow
285 provides for organisms overwintering in soil, cold microclimate temperatures can drop below a
286 species-specific cold tolerance threshold, which can result in mortality or sublethal cold injuries
287 (Bale, 1996; Sinclair et al., 2003). This result highlights the importance of snow cover variation
288 as a key factor in maintaining this variation and driving selection on genes associated with cold
289 tolerance and stress in winter.

290 Prior work in Sierra Nevada populations of *C. aeneicollis* shows that air temperature
291 varies between genetically differentiated populations and shows evidence of physiological
292 adaptation to different thermal regimes (Dahlhoff & Rank, 2000; 2007; Rank et al., 2008).
293 However, in the present study, the effect of ‘annual air temperature range’ (Fig 3) is largely
294 driven by climatic conditions in the Coast Range (CR). This broad thermal selective gradient
295 covaries with neutral patterns of population structure, which complicates distinctions between
296 neutral and selected loci (Nadeau et al., 2016); thus, the high detection rates observed in the
297 LFMM in the present study could also be due to residual, unaccounted population structure (Fig
298 4).

299 *Putative mechanisms of local adaptation to snow cover mirror mechanisms of cold tolerance*

300 Genes containing nonsynonymous SNPs associated with variation in snowfall encode proteins
301 with functions related to ion binding, actin and cytoskeleton binding and organization, and
302 membrane components; protein identifications were assigned with a high level of confidence, as
303 all homologous proteins are present in other beetle species (Table 3). These protein functions
304 align with previously identified mechanisms of cold tolerance and acclimation in both insects
305 and plants (Des Marteaux et al., 2018; Kim et al., 2006; Örvar et al., 2000; Pokorná et al., 2004).
306 Primary cellular challenges associated with deep and prolonged cold exposure or freezing
307 include loss of ion and water homeostasis and depolymerization of cytoskeletal components (e.g.
308 actin and tubulin), which can impair ion transport function, cause loss of cell junction integrity,
309 and exacerbate disturbances in membrane integrity caused by paracellular leaks of water and
310 ions (Cantiello, 1995; Khurana, 2000; Toxopeus & Sinclair, 2018; Turner et al., 1997). Cold-
311 acclimated insects are better able to maintain ion and water balance at low temperatures

312 compared to warm-acclimated insects (Overgaard & Macmillan, 2017), due to cellular structural
313 modifications that enhance cytoskeletal stability, thus protecting ionoregulatory tissues (e.g.
314 Malpighian tubules in insects) from chilling injury and loss of transport function (Des Marteaux
315 et al., 2018). Cold-acclimated insects also differentially regulate cytoskeletal gene expression,
316 with cold acclimation inducing upregulation of actin-associated genes or enzymes that promote
317 membrane and cytoskeletal remodeling (Des Marteaux et al., 2017; Kim et al., 2006; Toxopeus
318 et al., 2019). Because polymorphisms associated with variation in snowfall may relate to protein
319 modifications that enhance cytoskeletal and membrane stability in the cold, putative mechanisms
320 underlying local adaptation to snow are related to primary cellular mechanisms of cold
321 acclimation and tolerance. These results provide genomic evidence that variation in snowfall
322 imposes a selective gradient in exposure to cold stress, supporting the theory that snow
323 modulates cold stress and exposure for insects that overwinter in the soil (Roberts et al., 2021).

324 *Tandem genotype-environment association approach identifies signatures of local adaptation*

325 In detecting genomic signatures of local adaptation, genotype-environment associations
326 identified by various methods will depend strongly on demographic and sampling scenarios
327 (Forester et al., 2018; M. R. Jones et al., 2013; Nadeau et al., 2016; Rellstab et al., 2015).

328 Simulations conducted by Forester et al. 2016 find that multivariate ordination methods like
329 pRDA produce uniformly low false positive rates (0-2%), whereas LFMM produced high false
330 positive rates under low dispersal scenarios (Forester et al., 2016). *Chrysomela aeneicollis*
331 individuals have low levels of dispersal, with individuals often spending most of their life on a
332 single host plant (Rank, 1992b, 1994).

333 Nonetheless, correcting for population structure in pRDA can result in low power to
334 detect true associations (Lotterhos, 2023), and recent simulation modeling indicates that LFMM
335 provides the best compromise between detection power and error rates in situations with
336 complex hierarchical neutral genetic structure (De Villemereuil et al., 2014). Herbivorous insects
337 can have a subdivided population structure that reflects the distribution of their plant hosts
338 (Moraiti et al., 2014; Orrest & Thomson, 2011), and previous work found hierarchical,
339 subdivided genetic structure among patches and willows within a patch (Rank, 1992a). The
340 application of these two GEA methods highlights the trade-off between conservative and liberal
341 approaches in detecting a true adaptive signal, yet applying these methods in combination can
342 therefore yield increased confidence in true positive detections of local adaptation. Future work
343 should investigate the relationship between non-clinal allele frequency patterns and
344 environmental gradients, which can evolve under multivariate environments and can lead to
345 inaccurate inferences using GEA approaches (Lotterhos, 2023).

346 *Limitations*

347 A limitation of this study is sampling bias toward populations in the Sierra Nevada
348 ecoregion relative to the other three eco-regions included in this study (Fig 1), which may bias
349 genetic-environmental relationships and relative contributions of isolation by environment and
350 distance (Fig 2). Replicated sampling along environmental gradients increases confidence in true
351 positive detections of genotype-environmental associations (Rellstab et al., 2015), yet the
352 beetle's fragmented distribution in California limits replication across climatic conditions.
353 Another potential limitation is that temporal coverage of sampling was limited to one year in all
354 but the Sierra Nevada (SN) Ecoregions (Table 1), so that allele frequencies in these populations

355 may be influenced by environmental conditions in the collection year. Prior studies suggest that
356 genetic variation among SN, CB and CR populations has remained relatively stable since we last
357 sampled and analyzed them (Dellicour et al., 2014). We therefore expect that patterns reported
358 here reflect adaptation to long-term environmental conditions due to the geographic isolation
359 among populations.

360 Additionally, stringent SNP filter thresholds were applied to ensure quality genotypes
361 within each population, resulting in a relatively modest set of polymorphisms ($N = 22,323$
362 SNPs). While these thresholds did not alter overall estimates of population structure (Figs S3-
363 S5), candidate SNPs associated with environmental gradients in this study likely represent a
364 subset of loci involved in local adaptation.

365 *Conclusion*

366 Many montane species live on the periphery of both suitable habitat and physiological tolerance,
367 which contributes to the unique sensitivity of montane populations to climate change. Even small
368 environmental changes may result in large implications for survival and reproductive success
369 (Dahlhoff et al., 2019; Pepin et al., 2015; Stewart et al., 2017). The willow leaf beetle has
370 emerged as a natural model for analyzing the relationship between adaptive genetic variation and
371 environmental change (Dahlhoff et al., 2019; Dahlhoff & Rank, 2000; Rank, 1992a; Rank et al.,
372 2020b). By analyzing all known Californian *C. aeneicollis* populations across the nuclear
373 genome, this study represents the broadest investigation of adaptive genetic variation in the
374 species to date and provides a path forward for understanding the evolutionary significance of
375 variation at genes associated with response to environmental stress. Future work should identify
376 regions where genetic–environmental relationships will be most likely disrupted by climate

377 change and reduced snowfall, which will be critical for land management decisions and gene
378 conservation in vulnerable populations (Shaffer et al., 2022).

379

380 **Methods**

381 *Study populations and sampling design*

382 Ecoregions were identified following United States Geological Survey (USGS) designations
383 (Griffith et al., 2016). Beetle populations from the Sierra Nevada ecoregion were surveyed at
384 winter snowmelt (May-June) from 1996-2016, following methods detailed in Dahlhoff et al.
385 2019 (Appendix 1.1). In all, 175 individuals from 54 sampling locations were included and
386 assigned *a priori* to 12 populations (Table 1, Fig 1) based on previous work (Dellicour et al.,
387 2014a; Rank, 1992a; Rank et al., 2020a). These represent all known populations in California,
388 and they experience a wide range of seasonality, snow cover, and air temperature variation,
389 especially between montane and coastal regions (Table S3). Though allele frequencies can
390 fluctuate within a beetle population across years (Rank & Dahlhoff, 2002), the magnitude of
391 these fluctuations is relatively small compared to the magnitude of genetic divergence among
392 regions (Dahlhoff et al., 2008; Dellicour et al, 2014; Rank et al., 2020).

393 *DNA Library preparation and processing of genomic sequencing data*

394 Genomic DNA was extracted from individual beetles using NucleoMag Bacteria DNA Isolation
395 kit (Macherey-Nagel, Düren, Germany), and whole genome libraries were prepared following
396 the plexWell library preparation protocol by the CCGP MiniCore. Paired-end sequencing (2 x
397 150 bp) was performed on an Illumina HiSeq4000 platform at UC Berkeley's QB3 Genomics
398 Core Facility (Berkeley, CA, USA). Nextera adapter sequences and low-quality bases (base
399 quality < 15, sliding window 4 bp) were removed from each read using Trimmomatic v0.39
400 (Bolger et al., 2014). Reads were aligned to a *Chrysomela aeneicollis* reference genome
401 (Bracewell et al., 2023) using the Burrows-Wheeler Aligner (BWA-MEM) algorithm (Li &

402 Durbin, 2009). Joint genotyping was performed on all samples using Genome Analysis Toolkit
403 (GATK) v4.2.6.0 functions HaplotypeCaller and GenotypeGVCFs (Poplin et al., 2017). Variant
404 data were filtered to include only biallelic SNPs, and SNPs were hard-filtered using GATK best-
405 practice recommendations (Van der Auwera & O’Conner, 2020) (Table S2A). SNPs were
406 removed if minor allele frequency (MAF) across all individuals was less than 0.01 or if
407 heterozygote frequencies deviated greatly from Hardy Weinberg expectations (e.g., excess
408 heterozygosity or inbreeding coefficient greater than ± 0.5) (Table S2B). Finally, SNPs were
409 retained if 70% of all samples and 70% of samples within each population showed a read depth
410 between three and 30 and a genotype quality greater than 20 [Table S2C; (Xuereb et al., 2018)].
411 After filtering, principal components analysis (PCA) was performed on Hellinger-transformed
412 population-level minor allele frequencies (Legendre & Gallagher, 2001; Xuereb et al., 2018).
413 Because variant filter thresholds influence estimates of population structure (Linck & Battey,
414 2019; Pearman et al., 2022), we assessed sensitivity of genetic differentiation to filter threshold
415 levels.

416 *Microclimate variable simulation*

417 To obtain spatially explicit environmental variables representing local microclimate conditions
418 across the life cycle, microclimate simulations were conducted for the 12 beetle populations
419 using the biophysical modeling package *NicheMapR* (Kearney & Porter, 2017). The model
420 computes microclimatic conditions at a defined distance above ground, given local habitat
421 properties and weather conditions. The microclimate model was run using historical gridded
422 weather data from the GRIDMET daily weather database with 5 x 5 km resolution (Abatzoglou,
423 2013). The mid-latitude, -longitude, and -elevation of all demes within each population were

424 used as input in the model (Table 1, S2). The microclimate model was run in soil moisture and
425 snow modes under both minimum (10%) and maximum shade (90%) conditions for 1989-2020.
426 Simulated variables included air temperature and humidity at 1.75 m above the ground, snow-
427 related variables, and soil-related variables. To characterize mean environmental conditions,
428 daily microclimate variables were averaged over 30 simulated years (Table S3). We evaluated
429 sensitivity of simulated microclimate variables to input microclimate model parameters by
430 calculating RMSE between simulated outputs and empirically derived microclimate data from
431 available weather stations (California Department of Water Resources, CDEC). Air temperature
432 and snow depth data from CDEC were available for weather stations within 1 km of mid-
433 elevation sites in Rock Creek, Big Pine Creek, South Bishop Creek, and North Bishop Creek.

434 *Population genomic differentiation across the California landscape*

435 Population structure from SNP genotypic data was assessed by estimating proportions of
436 individual genomes originating from ancestral gene pools. A range of estimated ancestral gene
437 pools ($K = 1-10$) were tested using a sparse non-negative matrix factorization algorithm using the
438 function ‘snmf’ in the R package *LEA* v.3.6.0 [(Frichot et al., 2014; Frichot & François, 2015),
439 $K= 3-7$ shown in Fig S11]. The value of K that minimized cross-entropy and best explained
440 genotypic data was five [(Alexander & Lange, 2011), Fig S6] and this value was used for
441 subsequent analysis. The ‘snmf’ function was also used to estimate individual ancestry
442 coefficients. Five replicates were run using the best estimate of K , and individual ancestry
443 coefficients were extracted from the replicate with the lowest cross-entropy.

444 To quantify contributions of geographic and environmental distances to patterns of
445 genetic differentiation, we assessed isolation by distance (IBD) and isolation by environment

446 (IBE) for all population pairs using an analysis of covariance (ANCOVA). The ANCOVA tested
447 whether the means of pairwise F_{st} between populations were equal across habitat type, while
448 controlling geographic distance. Unbiased pairwise F_{st} using minor allele frequencies of all
449 populations were calculated using the R package *BEDASSLE* v.1.6 (Bradburd, 2022; Weir &
450 Hill, 2002). Pairwise geographic distance in kilometers was calculated using the R package *fields*
451 v.13.3 (Nychka & Furrer, 2021). Population pairs were identified as “coast vs. mountain” and
452 “mountain vs. mountain” to describe habitat type of populations, as this categorical descriptor
453 represents most environmental variation among populations (Table S3). Using the R package
454 *rstatix* v.0.7.1, ANCOVA was conducted with pair-wise F_{st} values as dependent variable, binary
455 environmental descriptor as categorical independent variable, and geographic distance as a
456 covariate. Least squares means were calculated for habitat types using the R package *emmeans*
457 v.1.8.3.

458 *Genotype-environment association tests to identify signatures of local adaptation*

459 Signatures of local adaptation to climate were investigated using two genotype-environment
460 association (GEA) methods, partial redundancy analysis [pRDA, (Borcard et al., 1992; Forester
461 et al., 2018; Peres-Neto et al., 2006)] and latent factor mixed modeling [LFMM, (Frichot et al.,
462 2013)], which control for signals generated by neutral processes through separate mechanisms.
463 Both GEA analyses were performed on two sets of populations: 1) all populations and 2) all
464 montane populations excluding the coastal (Gualala River) population. Partial redundancy
465 analysis (pRDA) was conducted at the population level since the resolution of environmental
466 data did not include environmental variation within a population. To account for isolation by
467 distance, we conducted a spatial eigenfunction analysis that produced a conditioning matrix in

468 the pRDA using distance-based Moran's eigenvector maps [Appendix 1.2, (Forester et al.,
469 2018b)]. All simulated environmental variables were scaled and centered to produce the
470 environmental matrix, and forward selection was used to select significant environmental
471 predictors, with significant dbMEMs as explanatory conditioning matrix and Hellinger-
472 transformed SNP minor allele frequencies as response matrix. The final pRDA was run with
473 significant ($\alpha < 0.05$) environmental predictors using the R package *vegan* v2.6-2 (Oksanen
474 et al., 2022). Outlier loci on constrained ordination axes were determined based on loadings of
475 each locus in ordination space (Forester et al., 2018; Xuereb et al., 2018).

476 We then conducted a latent factor mixed model (LFMM) and documented overlap of
477 detections with results from pRDA (Bay et al., 2018; De Villemereuil et al., 2014; Forester et al.,
478 2018; Nadeau et al., 2016). Neutral population structure due to shared demographic history or
479 background genetic variation is introduced through unobserved, latent factors (Frichot et al.,
480 2013). This method used individual-based genotypic data, which assessed the effect of *a priori*
481 designated populations used previously in pRDA. The 'lfmm' function in the *LEA* package was
482 implemented using individual-level genotypic data (22,323 SNPs) as response matrix, forward-
483 selected environmental variables used in pRDA as environmental predictors, and the best
484 estimate of K (estimated ancestral gene pools) as number of latent factors. More detailed GEA
485 methods are provided in Appendix 1.3.

486 *SNP and protein functional annotations*

487 We identified genes containing candidate SNPs and predicted SNP's coding effects with an
488 interval forest approach using the program SnpEff v.5.1 (Cingolani et al., 2012) and Caen 1.0
489 annotated genome (Bracewell et al., 2023). SNPs were annotated based on genomic location, and

490 coding effects were predicted (Appendix 1.4). To assign a putative protein name, protein
491 sequences were aligned to NCBI's protein database using BlastP (Table 3, S7, S10). Gene
492 Ontology (GO) terms were assigned to candidate genes using the functional annotation web
493 server database Protein ANNotation with Z-scoRE [PANNZER2, (Törönen et al., 2018)].
494

495 **Acknowledgements**

496 Beetle population samples used to conduct this research were the result of the dedicated effort of
497 over 90 undergraduate research assistants over the past 25 years. Efforts of Victoria Dahlhoff,
498 Jackie Leary, Alex Keil, and Jerry Zatorski are especially notable. We also thank Elliott Smeds,
499 Daniel Oliveira, Ana Lyons, Heath MacMillan, Jackie Lebenzon, Reema Aldaimalani and Kevin
500 Roberts for their valuable expertise and assistance in laboratory preparation and statistical
501 analyses. Samples were collected in accordance with United States Forest Service and California
502 Fish and Wildlife permitting guidelines. This work used the Vincent J. Coates Genomics
503 Sequencing Laboratory at University of California, Berkeley, supported by NIH S10 OD018174
504 Instrumentation Grant. This research was supported by grants from the National Science
505 Foundation (DEB 0844404/06 and IOS 1457335/395 to E. P. Dahlhoff and N. E. Rank) and the
506 California Conservation Genomics Project (C. M. Williams, E. Dahlhoff, N Rank, and Doris
507 Bachtrog, co-P.I.s).

508 **References**

- 509 Abatzoglou, J. T. (2013). Development of gridded surface meteorological data for ecological
510 applications and modelling. *International Journal of Climatology*, 33(1), 121–131.
511 <https://doi.org/10.1002/joc.3413>
- 512 Alexander, D. H., & Lange, K. (2011). Enhancements to the ADMIXTURE algorithm for
513 individual ancestry estimation. *BMC Bioinformatics*, 12, 246.
- 514 Bale, J. S. (1996). Insect cold hardiness: A matter of life and death. *European Journal of*
515 *Entomology*, 93, 369–382.
- 516 Bay, R., Harrigan, R., Underwood, V., Gibbs, H. L., Smith, T. B., & Ruegg, K. (2018). Genomic
517 signals of selection predict climate-driven population declines in a migratory bird.
518 *Science*, 359, 83–86.
- 519 Birrell, J. H., Shah, A. A., Hotaling, S., Giersch, J. J., Williamson, C. E., Jacobsen, D., & Woods,
520 H. A. (2020). Insects in high-elevation streams: Life in extreme environments imperiled
521 by climate change. *Global Change Biology*, 26(12), 6667–6684.
522 <https://doi.org/10.1111/gcb.15356>
- 523 Bolger, A. M., Lohse, M., & Usadel, B. (2014). Trimmomatic: A flexible trimmer for Illumina
524 Sequence Data. *Bioinformatics*, *btu170*.
- 525 Borcard, D., Legendre, P., & Drapeau, P. (1992). Partialling out the spatial component of
526 ecological variation. *Ecology*, 73(3), 1045–1055.
- 527 Boychuk, E. C., Smiley, J. T., Dahlhoff, E. P., Bernards, M. A., Rank, N. E., & Sinclair, B. J.
528 (2015). Cold tolerance of the montane Sierra leaf beetle, *Chrysomela aeneicollis*. *Journal*
529 *of Insect Physiology*, 81, 157–166.
- 530 Bracewell, R.R., Stillman, J.H., Dahlhoff, E.P., Smeds, E., Chatla, K., Bachtrog, D., Williams,
531 C., Rank, N.E. (2023). A chromosome-scale genome assembly and evaluation of mtDNA
532 variation in the willow leaf beetle *Chrysomela aeneicollis*. *G3 Genes|Genomes|Genetics*.
533 jkad106. <https://doi.org/10.1093/g3journal/jkad106>

534 Bradburd, G. (2022). *BEDASSLE: Quantifies Effects of Geo/Eco Distance on Genetic*
535 *Differentiation* (1.6). CRAN.R-project.org/package=BEDASSLE

536 Brown, W. J. (1956). The New World species of *Chrysomela* L. (Coleoptera: Chrysomelidae).
537 *The Canadian Entomologist*, 88, 1–54.

538 Camus, M. F. (2020). Digest: Mitonuclear interactions modulate life history phenotypes in the
539 wild. *Evolution*, 74(8), 1877–1878. <https://doi.org/10.1111/evo.13988>

540 Cantiello, F. (1995). Actin filaments stimulate the Na⁺-K⁺-ATPase. *American Journal of*
541 *Physiology - Renal Physiology*, 269(5), 637–643.

542 Cingolani, P., Platts, A., Wang, L. L., Coon, M., Nguyen, T., Wang, L., Land, S. J., Lu, X., &
543 Ruden, D. M. (2012). A program for annotating and predicting the effects of single
544 nucleotide polymorphisms, SnpEff: SNPs in the genome of *Drosophila melanogaster*
545 strain w1118; iso-2; iso-3. *Fly (Austin)*, 6(2), 80–92.

546 Conover, D. O. (1992). Seasonality and the scheduling of life history at different latitudes.
547 *Journal of Fish Biology*, 41, 161–178. [https://doi.org/10.1111/j.1095-](https://doi.org/10.1111/j.1095-8649.1992.tb03876.x)
548 [8649.1992.tb03876.x](https://doi.org/10.1111/j.1095-8649.1992.tb03876.x)

549 Dahlhoff, E. P., Dahlhoff, V. C., Grainger, C. A., Zavala, N. A., Otepola-Bello, D., Sargent, B.
550 A., Roberts, K. T., Heidl, S. J., Smiley, J. T., & Rank, N. E. (2019). Getting chased up the
551 mountain: High elevation may limit performance and fitness characters in a montane
552 insect. *Functional Ecology*, 33(5), 809–818. <https://doi.org/10.1111/1365-2435.13286>

553 Dahlhoff, E. P., Fearnley, S. L., Bruce, D. A., Gibbs, A. G., Stoneking, R., McMillan, D. M.,
554 Deiner, K., Smiley, J. T., & Rank, N. E. (2008). Effects of temperature on physiology and
555 reproductive success of a montane leaf beetle: Implications for persistence of native
556 populations enduring climate change. *Physiological and Biochemical Zoology*, 81(6),
557 718–732. <https://doi.org/10.1086/590165>

- 558 Dahlhoff, E. P., & Rank, N. E. (2000). Functional and physiological consequences of genetic
559 variation at phosphoglucose isomerase: Heat shock protein expression is related to
560 enzyme genotype in a montane beetle. *Proceedings of the National Academy of Sciences
561 of the United States of America*, 97(18), 10056–10061.
562 <https://doi.org/10.1073/pnas.160277697>
- 563 De Villemereuil, P., Frichot, E., Bazin, E., François, O., & Gaggiotti, O. E. (2014). Genome scan
564 methods against more complex models: When and how much should we trust them?
565 *Molecular Ecology*, 23(8), 2006–2019.
- 566 Dellicour, S., Fearnley, S. L., Lombal, A., Heidl, S. J., Dahlhoff, E. P., Rank, N. E., & Mardulyn,
567 P. (2014). Inferring the past and present connectivity across the range of a North
568 American leaf beetle: Combining ecological-niche modeling and a geographically
569 explicit model of coalescence. *Evolution*, 68, 2371–2385.
- 570 Des Marteaux, L. E., McKinnon, A. H., Udaka, H., Toxopeus, J., & Sinclair, B. J. (2017). Effects
571 of cold-acclimation on gene expression in Fall field cricket (*Gryllus pennsylvanicus*)
572 ionoregulatory tissues. *BMC Genomics*, 18(1), 1–17. [https://doi.org/10.1186/s12864-017-
573 3711-9](https://doi.org/10.1186/s12864-017-3711-9)
- 574 Des Marteaux, L. E., Stinziano, J. R., & Sinclair, B. J. (2018). Effects of cold acclimation on
575 rectal macromorphology, ultrastructure, and cytoskeletal stability in *Gryllus
576 pennsylvanicus* crickets. *Journal of Insect Physiology*, 104, 15–24.
577 <https://doi.org/10.1016/j.jinsphys.2017.11.004>
- 578 Dick, C. A., Rank, N. E., McCarthy, M., McWeeney, S., Hollis, D., & Dahlhoff, E. P. (2013).
579 Effects of temperature variation on male behavior and mating success in a montane
580 beetle. *Physiological and Biochemical Zoology*, 86(4), 432–440.
- 581 Felsenstein, J. (1976). The theoretical population genetics of variable selection and migration.
582 *Annual Review of Genetics*, 10, 253–280.
- 583 Forester, B. R., Jones, M. R., Joost, S., Landguth, E. L., & Lasky, J. R. (2016). Detecting spatial
584 genetic signatures of local adaptation in heterogeneous landscapes. *Molecular Ecology*,
585 25(1), 104–120. <https://doi.org/10.1111/mec.13476>

- 586 Forester, B. R., Lasky, J., Wagner, H., & Urban, D. L. (2018). Comparing methods for detecting
587 multilocus adaptation with multivariate genotype–environment associations. *Molecular*
588 *Ecology*, 27(9), 2215–2233.
- 589 Fretwell, S. D. (1972). Populations in a seasonal environment. *Monographs in Population*
590 *Biology*, 5, 1–217.
- 591 Frichot, E., & François, O. (2015). LEA: An R package for landscape and ecological association
592 studies. *Methods in Ecology and Evolution*, 6(8), 925–929.
- 593 Frichot, E., Mathieu, F., Trouillon, T., Bouchard, G., & François, O. (2014). Fast and efficient
594 estimation of individual ancestry coefficients. *Genetics*, 196, 973–983.
- 595 Frichot, E., Schoville, S. D., Bouchard, G., & François, O. (2013). Testing for associations
596 between loci and environmental gradients using latent factor mixed models. *Molecular*
597 *Biology and Evolution*, 30, 1687–1699.
- 598 Griffith, G. E., Omernik, J. M., Smith, D. W., Cook, T. D., Tallyn, E., Moseley, K., & Johnson,
599 C. B. (2016). *Ecoregions of California: U.S. Geological Survey Open-File Report 2016–*
600 *1021, with map, scale 1:1,100,000.*
- 601 Groffman, P. M., Driscoll, C. T., Fahey, T. J., Hardy, J. P., Fitzhugh, R. D., & Tierney, G. L.
602 (2001). Colder soils in a warmer world: A snow manipulation study in a northern
603 hardwood forest ecosystem. *Biogeochemistry*, 56(2), 135–150.
604 <https://doi.org/10.1023/A:1013039830323>
- 605 Halsch, C. A., Shapiro, A. M., Fordyce, J. A., Nice, C. C., Thorne, J. H., Waetjen, D. P., &
606 Forister, M. L. (2021). Insects and recent climate change. *Proceedings of the National*
607 *Academy of Sciences of the United States of America*, 118(2), 1–9.
608 <https://doi.org/10.1073/PNAS.2002543117>
- 609 Haldane, J.B.S., Jayakar, S.D. (1963). Polymorphism due to selection in varying directions.
610 *Journal of Genetics*. 58: 237-242.
- 611 Hedrick, P. W., Ginevan, M. E., & Ewing, E. P. (1976). Genetic polymorphism in heterogeneous
612 environments. *Annual Review of Ecology, Evolution, and Systematics*, 7, 1–32.

613 Huning, L. S., & AghaKouchak, A. (2020). Global snow drought hot spots and characteristics.
614 *Proceedings of the National Academy of Sciences of the United States of America*,
615 *117*(33), 19753–19759. <https://doi.org/10.1073/PNAS.1915921117>

616 Jones, M. R., Forester, B. R., Teufel, A. I., Adams, R. V., Anstett, D. N., Goodrich, B. A.,
617 Landguth, E. L., Joost, S., & Manel, S. (2013). Integrating landscape genomics and
618 spatially explicit approaches to detect loci under selection in clinal populations.
619 *Evolution*, *67*(12), 3455–3468. <https://doi.org/10.1111/evo.12237>

620 Kawecki, T., & Ebert, D. (2004). Conceptual issues in local adaptation. *Ecology Letters*, *7*(12),
621 1225–1241.

622 Kearney, M. R., & Porter, W. P. (2017). NicheMapR – an R package for biophysical modelling:
623 The microclimate model. *Ecography*, *40*(5), 664–674. <https://doi.org/10.1111/ecog.02360>

624 Khurana, S. (2000). Role of actin cytoskeleton in regulation of ion transport: Examples from
625 epithelial cells. *Journal of Membrane Biology*, *178*(2), 73–87.
626 <https://doi.org/10.1007/s002320010016>

627 Kim, M., Robich, R. M., Rinehart, J. P., & Denlinger, D. L. (2006). Upregulation of two actin
628 genes and redistribution of actin during diapause and cold stress in the northern house
629 mosquito, *Culex pipiens*. *Journal of Insect Physiology*, *52*(11–12), 1226–1233.
630 <https://doi.org/10.1016/j.jinsphys.2006.09.007>

631 Larsen, T.H. (2012). Upslope range shifts of Andean dung beetles in response to deforestation:
632 Compounding and confounding effects of microclimatic change. *Biotropica*. *44*: 82-89.

633 Legendre, P., & Gallagher, E. D. (2001). Ecologically meaningful transformations for ordination
634 of species data. *Oecologia*, *129*, 271–280.

635 Lotterhos, K.E. (2023). The paradox of adaptive trait clines with nonclinal patterns in the
636 underlying genes. *Proceedings of the National Academy of Sciences of the United States*
637 *of America*, *120*(12): e2220313120.

638 Li, H., & Durbin, R. (2009). Fast and accurate short read alignment with Burrows–Wheeler
639 transform. *Bioinformatics*, *25*(14), 1754–1760.

640 Linck, E., & Battey, C. J. (2019). Minor allele frequency thresholds strongly affect population
641 structure inference with genomic data sets. *Molecular Ecology Resources*, 19(3), 639–
642 647. <https://doi.org/10.1111/1755-0998.12995>McMillan, D. M., Fearnley, S. L., Rank, N.
643 E., & Dahlhoff, E. P. (2005). Natural temperature variation affects larval survival,
644 development and Hsp70 expression in a leaf beetle. *Functional Ecology*, 19(5), 844–852.

645 Millstein, R. (2006). Natural Selection as a Population-Level Causal Process. *The British Journal*
646 *for the Philosophy of Science*, 57(4), 627–653.

647 Moraiti, C. A., Nakas, C. T., & Papadopoulos, N. T. (2014). Diapause termination of *Rhagoletis*
648 *cerasi* pupae is regulated by local adaptation and phenotypic plasticity: Escape in time
649 through bet-hedging strategies. *Journal of Evolutionary Biology*, 27(1), 43–54.
650 <https://doi.org/10.1111/jeb.12273>

651 Moret, P., Arauz, M.D., Gobbi, M., Barragan, A. (2016). Climate warning effects in the tropical
652 Andes: First evidence for upslope shifts of Carabidae (Coleoptera) in Ecuador. *Insect*
653 *Conservation and Diversity*. 9: 342-350.

654 Mote, P. W., Li, S., Lettenmaier, D. P., Xiao, M., & Engel, R. (2018). Dramatic declines in
655 snowpack in the western US. *Npj Climate and Atmospheric Science*, 1(1), 2.
656 <https://doi.org/10.1038/s41612-018-0012-1>

657 Nadeau, S., Meirmans, P., Aitken, S., Ritland, K., & Isabel, N. (2016). The challenge of
658 separating signatures of local adaptation from those of isolation by distance and
659 colonization history: The case of two white pines. *Ecology and Evolution*, 6(24), 8649–
660 8664.

661 Nearing, G., Dahlhoff, E. P., & Rank, N. E. (2003). Variation in thermal tolerance is linked to
662 phosphoglucose isomerase genotype in a montane leaf beetle. *Functional Ecology*, 17(2),
663 213–221. <https://doi.org/10.1046/j.1365-2435.2003.00722.x>

664 Nychka, D., & Furrer, R. (2021). *fields: Tools for spatial data* (13.3). University Corporation for
665 Atmospheric Research. <https://github.com/dnychka/fieldsRPackage>

666 Oksanen, J., Simpson, G. L., Blanchet, F. G., Kindt, R., Legendre, P., Minchin, P. R., O'Hara, R.
667 B., Solymos, P., Stevens, M. H. H., Szoecs, E., Wagner, H., Barbour, M., Bedward, M.,
668 Bolker, B., Borcard, D., Carvalho, G., Chirico, M., Durand, S., Evangelista, H. B. A., ...
669 Cajo, J. F. (2022). *vegan: Community Ecology Package (2.6-2)*. [https://CRAN.R-](https://CRAN.R-project.org/package=vegan)
670 [project.org/package=vegan](https://CRAN.R-project.org/package=vegan)

671 Orrest, J. R. K., & Thomson, J. D. (2011). An examination of synchrony between insect
672 emergence and flowering in Rocky Mountain meadows. *Ecological Monographs*, *81*(3),
673 469–491.

674 Orsini, L., Vanoverbeke, J., Swillen, I., Mergeay, J., & De Meester, L. (2013). Drivers of
675 population genetic differentiation in the wild: Isolation by dispersal limitation, isolation
676 by adaptation and isolation by colonization. *Molecular Ecology*, *22*(24), 5983–5999.
677 <https://doi.org/10.1111/mec.12561>

678 Örvar, B. L., Sangwan, V., Omann, F., & Dhindsa, R. S. (2000). Early steps in cold sensing by
679 plant cells: The role of actin cytoskeleton and membrane fluidity. *Plant Journal*, *23*(6),
680 785–794. <https://doi.org/10.1046/j.1365-313X.2000.00845.x>

681 Otto, S. B., Berlow, E. L., Rank, N. E., Smiley, J., & Brose, U. (2008). Predator diversity and
682 identity drive interaction strength and trophic cascades in a food web. *Ecology*, *89*(1),
683 134–144.

684 Overgaard, J., & Macmillan, H. A. (2017). The integrative physiology of insect chill tolerance.
685 *Annual Review of Physiology*, *79*, 187–208. [https://doi.org/10.1146/annurev-physiol-](https://doi.org/10.1146/annurev-physiol-022516-034142)
686 [022516-034142](https://doi.org/10.1146/annurev-physiol-022516-034142)

687 Pauli, J. N., Zuckerberg, B., Whiteman, J. P., & Porter, W. (2013). The subnivium: A
688 deteriorating seasonal refugium. *Frontiers in Ecology and the Environment*, *11*(5), 260–
689 267. <https://doi.org/10.1890/120222>

690 Pearman, W. S., Urban, L., & Alexander, A. (2022). Commonly used Hardy–Weinberg
691 equilibrium filtering schemes impact population structure inferences using RADseq data.
692 *Molecular Ecology Resources*, *22*, 2599–2613. <https://doi.org/10.1111/1755-0998.13646>

- 693 Pepin, N., Bradley, R. S., Diaz, H. F., Baraer, M., Caceres, E. B., Forsythe, N., Fowler, H.,
694 Greenwood, G., Hashmi, M. Z., Liu, X. D., Miller, J. R., Ning, L., Ohmura, A., Palazzi,
695 E., Rangwala, I., Schöner, W., Severskiy, I., Shahgedanova, M., Wang, M. B., ... Yang,
696 D. Q. (2015). Elevation-dependent warming in mountain regions of the world. *Nature*
697 *Climate Change*, 5(5), 424–430. <https://doi.org/10.1038/nclimate2563>
- 698 Peres-Neto, P. R., Legendre, P., Dray, S., & Borcard, D. (2006). Variation partitioning of species
699 data matrices: Estimation and comparison of fractions. *Ecology*, 87, 2614–2625.
- 700 Pokorná, J., Schwarzerová, K., Zelenková, S., Petrášek, J., Janotová, I., Čapková, V., & Opatrný,
701 Z. (2004). Sites of actin filament initiation and reorganization in cold-treated tobacco
702 cells. *Plant, Cell and Environment*, 27(5), 641–653. [https://doi.org/10.1111/j.1365-](https://doi.org/10.1111/j.1365-3040.2004.01186.x)
703 [3040.2004.01186.x](https://doi.org/10.1111/j.1365-3040.2004.01186.x)
- 704 Poplin, R., Ruano-Rubio, V., DePristo, M. A., Fennell, T. J., Carneiro, M. O., Van der Auwera,
705 G. A., Kling, D. E., Gauthier, L. D., Levy-Moonshine, A., Roazen, D., Shakir, K.,
706 Thibault, J., Chandran, S., Whelan, C., Lek, M., Gabriel, S., Daly, M. J., Neale, B.,
707 MacArthur, D. G., & Banks, E. (2017). Scaling accurate genetic variant discovery to tens
708 of thousands of samples. *BioRxiv*, 201178.
- 709 Rank, N. E. (1992a). A hierarchical analysis of genetic differentiation in a montane leaf beetle
710 (*Chrysomela aeneicollis*). *Evolution*, 46, 1097–1111.
- 711 Rank, N. E. (1992b). Host plant preference based on salicylate chemistry in a willow leaf beetle
712 (*Chrysomela aeneicollis*). *Oecologia*, 90(1), 95–101.
713 <https://doi.org/10.1007/BF00317814>
- 714 Rank, N. E. (1994). Host-Plant Effects on Larval Survival of a Salicin-Using Leaf Beetle
715 *Chrysomela aeneicollis* Schaeffer (Coleoptera: Chrysomelidae). *Oecologia*, 97(3), 342–
716 353.
- 717 Rank, N. E., & Dahlhoff, E. P. (2002). Allele frequency shifts in response to climate change and
718 physiological consequences of allozyme variation in a montane insect. *Evolution*, 56(11),
719 2278–2289.

- 720 Rank, N. E., Mardulyn, P. M., Heidl, S. J., Roberts, K. T., Zavala, N. A., & Dahlhoff, E. P.
721 (2020). Mitonuclear mismatch alters performance and reproductive success in naturally
722 introgressed populations of a montane leaf beetle. *Evolution*, 74(8), 1724–1740.
- 723 Rellstab, C., Gugerli, F., Eckert, A. J., Hancock, A. M., & Holderegger, R. (2015). A practical
724 guide to environmental association analysis in landscape genomics. *Molecular Ecology*,
725 24(17), 4348–4370. <https://doi.org/10.1111/mec.13322>
- 726 Rhomberg, L. R., & Singh, R. S. (1986). Evidence for a link between local and seasonal cycles
727 in gene frequencies and latitudinal gene clines in a cyclic parthenogen. *Genetica*, 78(1),
728 73–79. <https://doi.org/10.1007/BF00058677>
- 729 Roberts, K. T., Rank, N. E., Dahlhoff, E. P., Stillman, J. H., & Williams, C. M. (2021). Snow
730 modulates winter energy use and cold exposure across an elevation gradient in a montane
731 ectotherm. *Global Change Biology*, 27(23), 6103–6116.
732 <https://doi.org/10.1111/gcb.15912>
- 733 Shafer, A. B. A., & Wolf, J. B. W. (2013). Widespread evidence for incipient ecological
734 speciation: A meta-analysis of isolation-by-ecology. *Ecology Letters*, 16(7), 940–950.
735 <https://doi.org/10.1111/ele.12120>
- 736 Shaffer, H. B., Toffelmier, E., Corbett-Detig, R. B., Escalona, M., Erickson, B., Fiedler, P., Gold,
737 M., Harrigan, R. J., Hodges, S., Luckau, T. K., Miller, C., Oliveira, D. R., Shaffer, K. E.,
738 Shapiro, B., Sork, V. L., & Wang, I. J. (2022). Landscape genomics to enable
739 conservation actions: The California Conservation Genomics Project. *Journal of*
740 *Heredity*, esac020. <https://doi.org/10.1093/jhered/esac020>
- 741 Shah, A. A., Dillon, M. E., Hotaling, S., & Woods, H. A. (2020). High elevation insect
742 communities face shifting ecological and evolutionary landscapes. *Current Opinion in*
743 *Insect Science*, 41, 1–6. <https://doi.org/10.1016/j.cois.2020.04.002>
- 744 Sinclair, B. J., Vernon, P., Klok, C. J., & Chown, S. L. (2003). Insects at low temperatures: An
745 ecological perspective. *Trends in Ecology and Evolution*, 18(5), 257–262.
- 746 Slatkin, M. (1987). Gene flow and the geographic structure of natural populations. *Science*, 236,
747 787–792.

748 Slatyer, R. A., Umbers, K. D. L., & Arnold, P. A. (2022). Ecological responses to variation in
749 seasonal snow cover. *Conservation Biology*, 36(1). <https://doi.org/10.1111/cobi.13727>

750 Smiley, J. T., & Rank, N. E. (1986). Predator protection versus rapid growth in a montane leaf
751 beetle. *Oecologia*, 70, 106–112.

752 Sork, V. L., Aitken, S. N., Dyer, R. J., Eckert, A. J., Legendre, P., & Neale, D. B. (2013). Putting
753 the landscape into the genomics of trees: Approaches for understanding local adaptation
754 and population responses to changing climate. *Tree Genetics and Genomes*, 9(4), 901–
755 911. <https://doi.org/10.1007/s11295-013-0596-x>

756 Stewart, J. A. E., Wright, D. H., & Heckman, K. A. (2017). Apparent climate-mediated loss and
757 fragmentation of core habitat of the American pika in the Northern Sierra Nevada,
758 California, USA. *PLoS ONE*, 12(8), 1–18. <https://doi.org/10.1371/journal.pone.0181834>

759 Törönen, P., Medlar, A., & Holm, L. (2018). PANNZER2: A rapid functional annotation web
760 server. *Nucleic Acids Research*, 46(W1), W84–W88.

761 Toxopeus, J., Des Marteaux, L. E., & Sinclair, B. J. (2019). How crickets become freeze tolerant:
762 The transcriptomic underpinnings of acclimation in *Gryllus veletis*. *Comparative*
763 *Biochemistry and Physiology - Part D*, 29, 55–66.
764 <https://doi.org/10.1016/j.cbd.2018.10.007>

765 Toxopeus, J., & Sinclair, B. J. (2018). Mechanisms underlying insect freeze tolerance. *Biological*
766 *Reviews*, 93(4), 1891–1914.

767 Turner, J. R., Rill, B. K., Carlson, S. L., Carnes, D., Kerner, R., Mrsny, R. J., & Madara, J. L.
768 (1997). Physiological regulation of epithelial tight junctions is associated with myosin
769 light-chain phosphorylation. *American Journal of Physiology - Cell Physiology*, 273(4),
770 C1378-1385. <https://doi.org/10.1152/ajpcell.1997.273.4.c1378>

771 Van der Auwera, G. A., & O’Conner, B. D. (2020). *Genomics in the Cloud: Using Docker,*
772 *GATK, and WDL in Terra* (1st Edition). O’Reilly Media.

773 Wang, I. J., & Bradburd, G. S. (2014). Isolation by environment. *Molecular Ecology*, 23(23),
774 5649–5662. <https://doi.org/10.1111/mec.12938>

- 775 Weir, B. S., & Hill, W. G. (2002). Estimating F-statistics. *Ann. Rev. Gen.*, 36, 949–952.
- 776 Williams, C. M., Henry, H. A. L., & Sinclair, B. J. (2015). Cold truths: How winter drives
777 responses of terrestrial organisms to climate change. *Biological Reviews*, 90(1), 214–235.
778 <https://doi.org/10.1111/brv.12105>
- 779 Williams, C. M., Ragland, G. J., Betini, G., Buckley, L. B., Cheviron, Z. A., Donohue, K.,
780 Hereford, J., Humphries, M. M., Lisovski, S., Marshall, K. E., Schmidt, P. S., Sheldon,
781 K. S., Varpe, Ø., & Visser, M. E. (2017). Understanding evolutionary impacts of
782 seasonality: An introduction to the symposium. *Integrative and Comparative Biology*,
783 57(5), 921–933. <https://doi.org/10.1093/icb/icx122>
- 784 Wittman, M.J., Bergland, A.O., Feldman, M.W., Schmidt, P.S., Petrov, D.A. (2017). Seasonally
785 fluctuating selection can maintain polymorphism at many loci via segregation lift.
786 *Proceedings of the National Academy of Sciences of the United States of America*,
787 114(46): e9932-e9941.
- 788 Xuereb, A., Kimber, C., Curtis, J., Bernatchez, L., & Fortin, M. J. (2018). Putatively adaptive
789 genetic variation in the giant California sea cucumber (*Parastichopus californicus*) as
790 revealed by environmental association analysis of restriction-site associated DNA
791 sequencing data. *Molecular Ecology*, 27(24), 5035–5018.
- 792
- 793

794 **Tables**

795

796 **Table 1. Localities and sample sizes for population genomic studies.**

<i>Ecoregion</i> Population name	Latitude	Longitude	Elevation (m)	<i>N</i> sites	<i>N</i> beetles (total)	Year(s) ¹
<i>Sierra Nevada</i>						
Tuttle Creek (TC)	36.53779	-118.21530	3012	1	10	2019
Taboose Pass (TP)	36.96824	-118.43419	3321	3	18	2009
Big Pine Creek (BP)	37.12863	-118.48704	3142	11	28	1998-2014
Baker Creek (BK)	37.16780	-118.47143	3120	3	18	1999
S Bishop Creek (BC)	37.16601	-118.55171	3098	14	38	2004-2014
Tyee Lakes (TL)	37.18567	-118.57565	3191	4	9	2014
N Bishop Creek (NF)	37.21760	-118.64757	3131	6	12	2003-2014
Pine Creek (PC)	37.34442	-118.72861	3057	2	4	2013
Rock Creek (RC)	37.45561	-118.74034	3030	5	10	2013-2014
<i>Central Basin</i>						
Davis Creek (DC)	37.78392	-118.23650	2895	1	12	2003
<i>Eastern Cascades</i>						
Fitzhugh Creek (FC)	41.35091	-120.29662	1968	3	11	2020
<i>Coast Range</i>						
Gualala River (GR)	38.74906	-123.51919	12	1	8	2016

797 ¹We sampled newly emerged overwintered adults, either from the most recent population

798 expansion (2013-14), or the most recent observation of overwintered beetles at that site. Further

799 details of sampling design are described in Appendix 1.1.

800 **Table 2. Candidate SNPs correlated with microclimate variables.** Total number of SNPs are
 801 shown. For genic SNPs, the number of unique genes containing at least one non-synonymous
 802 (NSY) or synonymous (SYN) substitution, as well as genes where the SNP is located in an
 803 intron, are also indicated. Candidate SNPs and genes are delineated by identification through
 804 analyses with montane and coastal populations or analyses with only montane populations.

Microclimate variable	Populations	Detection Method	Number of SNPs		Number of genes		
			Total	Genic	NonSyn	Syn	Intron
Air temperature range	Montane & coastal	pRDA & LFMM	67	33	4	11	18
		pRDA only	70	33	4	11	18
Maximum daily snowfall	Montane & coastal	pRDA & LFMM	26	16	4	4	4
		pRDA only	39	21	5	4	7
Maximum daily snowfall	Montane only	pRDA & LFMM	79	40	4	10	11
		pRDA only	116	62	8	13	15

805
806

807 **Table 3. Candidate proteins that vary with microclimate.** Proteins were identified using
 808 BlastP alignment using predicted amino acid sequence; associated NCBI accession number is
 809 noted for sequence with highest homology to reference taxa; populations included in analysis
 810 (montane and coastal, montane only, or both) are indicated.

Gene ID	Amino acid variants	Protein	Reference sequence (taxa ^A , % identity) Accession number	Gene Ontology (GO) terms ^B
Air temperature range				
<i>Montane & Coastal</i>				
05_00.257	Val/Ile	nuclear valosin-containing protein-like	<i>Ld</i> : 99, 71 XP_023023254.1	ATP binding and hydrolysis ² ribosome binding ² , biogenesis ³ telomerase activity ³
06_05.960	Asn/His	cytochrome P450 315a1, mitochondrial	<i>Ld</i> : 100, 58 XP_023020072.1	Monooxygenase, oxidoreductase activity ² ; ecdysone biosynthesis ³
15_02.330	Leu/Phe	phospholipid transfer protein	<i>Ag</i> : 100, 75 XP_018561647.1	membrane ¹ nucleotidyl trans. activity ² phosphorylation, signal transduction ³
Maximum daily snowfall				
<i>Montane & Coastal</i>				
02_12.369	Ser/Gly	transmembrane protein 131	<i>Ld</i> : 94, 66 XP_023015832.1	membrane ¹
14_11.590	Val/Ala	testin ^C	<i>Tg</i> : 100, 63 XP_008194458.1	zinc ion binding ²
<i>Montane only</i>				
02_16.309	Ser/Pro	long-chain-fatty-acid CoA ligase	<i>Ld</i> : 99, 76 XP_023012248.1	ligase activity ² , lipid metabolic process ³ , neuron cellular homeostasis ³
03_01.420	Val/Leu	protein pigeon (PION) ^C	<i>Ld</i> : 100, 73 XP_023019414.1	regulation of membrane protein (amyloid-beta) formation ³
03_04.184	Asn/Asp	ankyrin repeat; IBR domain-containing protein ^C	<i>Ag</i> : 98, 81 XP_018576173.1	metal ion binding ² , ubiquitin-protein transferase activity ² , protein ubiquitination ³
04_00.113	Ile/Val	zinc transporter ZIP-1 like isoform ^C	<i>Ld</i> : 100, 67 XP_023015018.1	metal ion transmembrane transporter activity ^{2,3}
18_04.151	Asn/Thr	ribosomal protein	<i>Ld</i> : 100, 68 XP_023030475.1	ribosome ¹ , translation ³
<i>Montane & Coastal + Montane only</i>				
10_13.168	Glu/Asp ^y Pro/Ala ^y	inverted formin-2	<i>Ag</i> : 98, 63 XP_023310886.1	actin cytoskeleton organization ²
20_03.324	Gln/His	microtubule-actin cross-linking factor	<i>Dv</i> : 45, 69 XP_028131989.1	membrane ¹ , cytoskeleton ¹ Ca ⁺⁺ ion binding ² , microtubule binding ² ; cytoskeleton organization ³

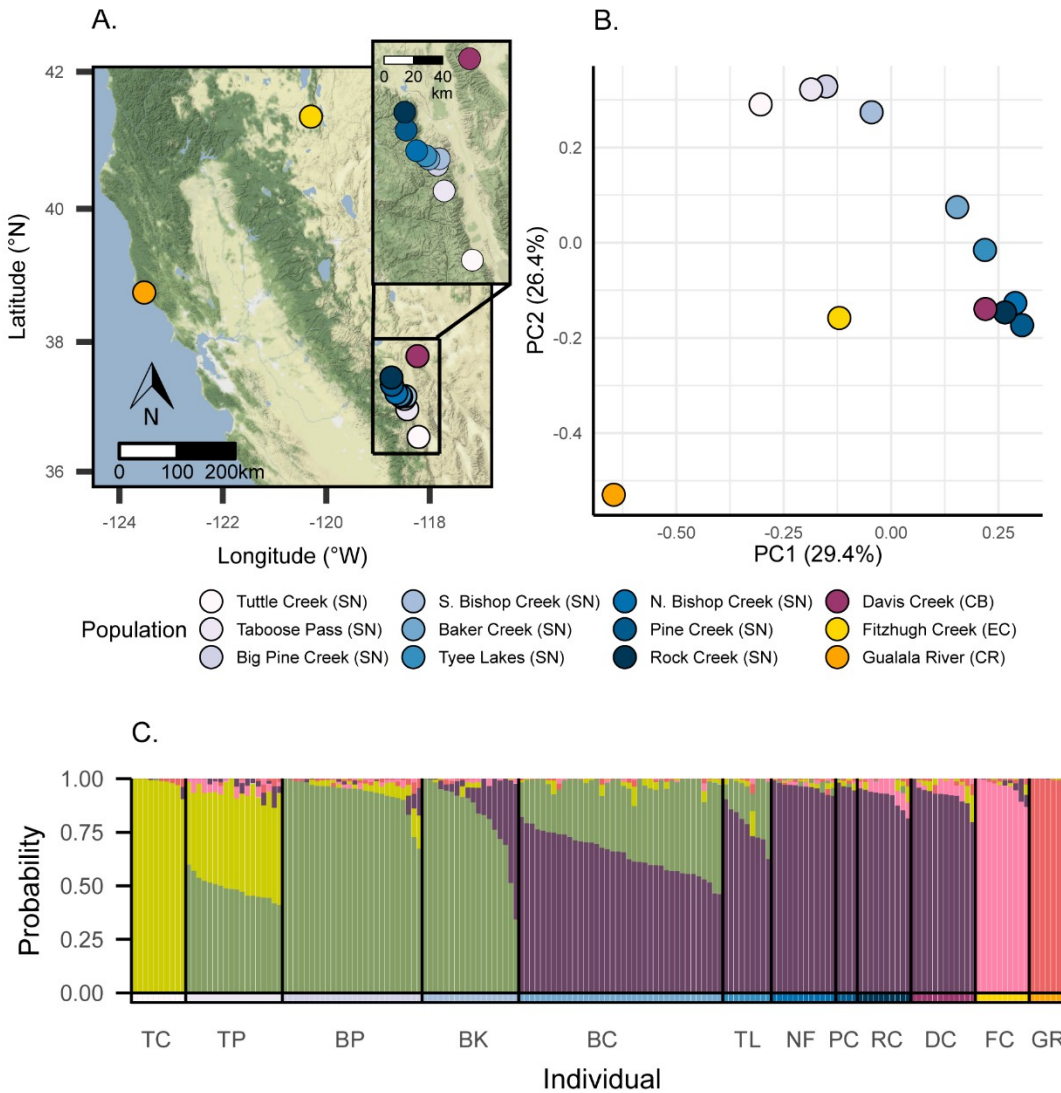
811 ^AReference taxa: *Leptinotarsa decemlineata* (*Ld*: Colorado potato beetle), *Anoplophora glabripennis* (*Ag*: Asian
 812 long-horned beetle), *Tribolium castaneum* (*Tc*: Red flour beetle), *Diabrotica virgifera* (*Dv*: Corn rootworm beetle).

813 ^BGO Term Categories: cellular component¹, molecular function², biological process³

814 ^CSNP only detected with pRDA; ^ySNP locations directly adjacent (Table S6)

815

816 **Figures**
817



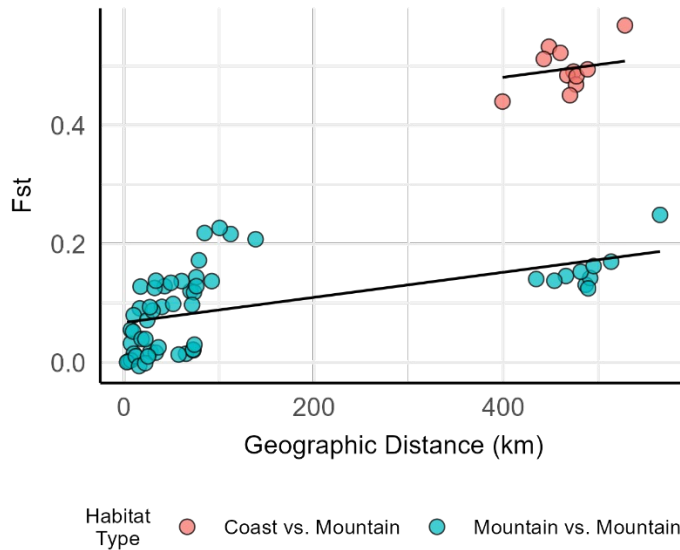
818
819

820 **Figure 1. Genetic differentiation and structure of *Chrysomela aeneicollis* populations across**
821 **California.** **A.** Map of study populations. Abbreviation in parenthesis refers to population
822 ecoregion (SN: Sierra Nevada, CB: Central Basin, EC: Eastern Cascades, CR: Coast Range).
823 Inset map features the sampled populations located in the Sierra Nevada and Central Basin
824 ecoregions. Populations in the Sierra Nevada ecoregion are presented using a blue color gradient
825 and are ordered based by latitude, south to north, representing increasing latitude. **B.** PCA

826 ordination highlighting genomic differentiation among populations based on the minor allele
827 frequencies. *C.* Stacked barplots for each individual ($N = 175$ total) indicate estimated ancestry
828 coefficients, representing the posterior probability that an individual originates from $K = 5$
829 ancestral gene pools. Colors below the stacked barplot indicate each individual's a priori
830 population designations, as shown in parts *A* and *B*. Two-letter population designations are
831 described in Table 1.

832

833
834



835
836

Figure 2. Genomic differentiation as a function of geographic distance and habitat type for

837 **California willow beetle populations.** Data shown highlight the relationship between pairwise

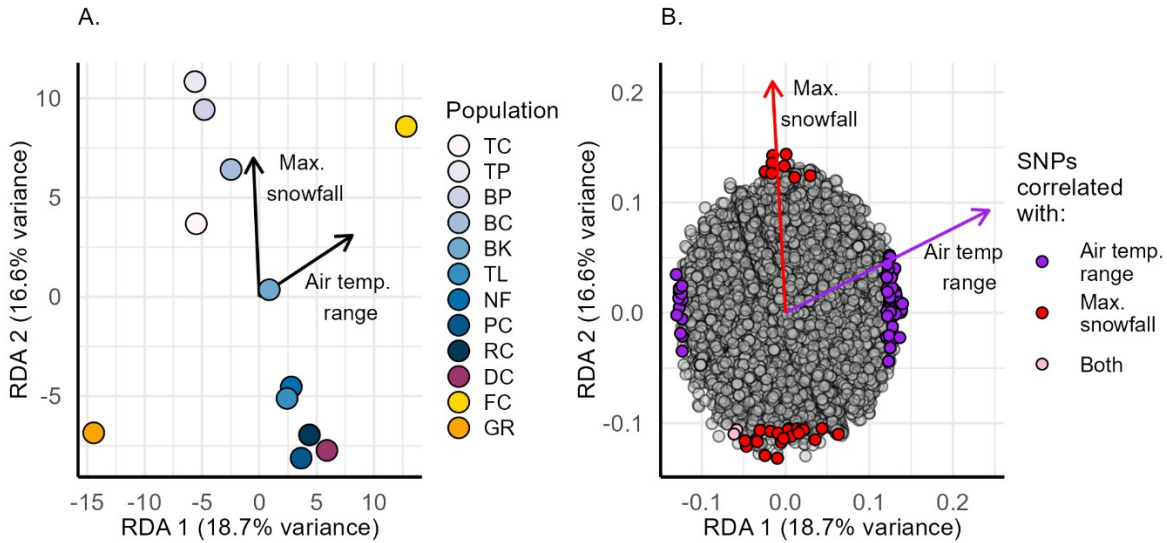
838 geographic distance (km) and pairwise genetic distance (*Fst*). The black lines indicate the fitted

839 values from the ANCOVA model, and points are color coded by the categorical independent

840 variable used in the ANCOVA model.

841

842



843

844 **Figure 3. Partial redundancy analysis (pRDA) identifies candidate loci associated with**

845 **selective climatic gradients. A.** Ordination of populations and environmental variable loadings

846 in multivariate space. Environmental variable loadings are multiplied by 10 to improve

847 visualization. **B.** Ordination of SNP loci and environmental variable loadings in multivariate

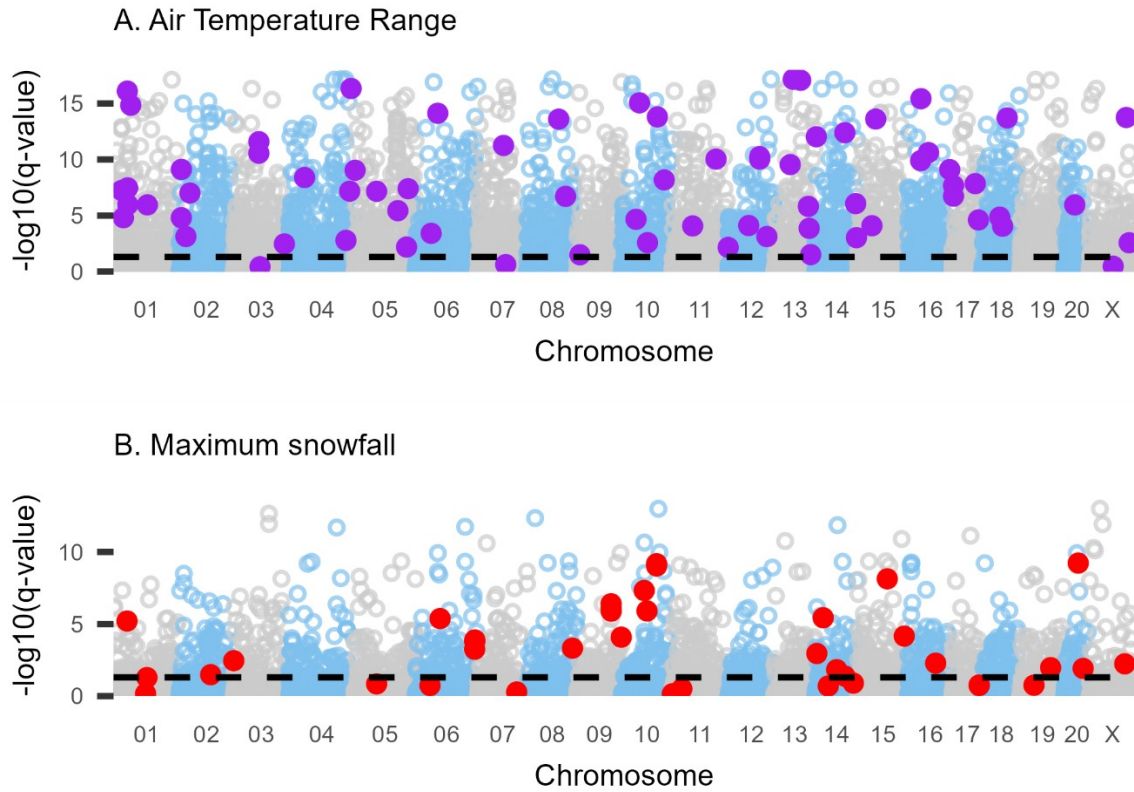
848 space. Outlier loci are colored based on correlation with an environmental variable (Pearson's $r >$

849 $|0.65|$). Environmental variable loadings are multiplied by 0.4 to improve visualization. Two-

850 letter population designations are described in Table 3. Results of pRDA with only montane

851 populations are provided in Figure S7.

852



853
 854 **Figure 4. Latent factor mixed model (LFMM) identifies candidate loci associated with**
 855 **selective climatic gradients.** Points indicate the FDR-adjusted p-value (q-value) of the
 856 association between a locus and an environmental gradient. The dotted black line represents a q-
 857 value of 0.05, and purple and red colored loci are those detected by the pRDA. **A.** Loci
 858 associations with annual air temperature range. **B.** Loci associations with maximum daily
 859 snowfall. Results of LFMM with only montane populations are provided in Figure S8.
 860