



Thermal reactionomes reveal divergent responses to thermal extremes in warm and cool-climate ant species

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2 thermal extremes in warm and cool-climate ant species

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Abstract

Background The distributions of species and their responses to climate change are in part determined by their thermal tolerances. However, little is known about how thermal tolerance evolves. To test whether evolutionary extension of thermal limits is accomplished through enhanced cellular stress response (*enhanced response*), constitutively elevated expression of protective genes (*genetic assimilation*) or a shift from damage resistance to passive mechanisms of thermal stability (*tolerance*), we conducted an analysis of the *reactionome*: the reaction norm for all genes in an organism’s transcriptome measured across an experimental gradient. We characterized thermal reactionomes of two common ant species in the eastern U.S, the northern cool-climate *Aphaenogaster picea* and the southern warm-climate *Aphaenogaster carolinensis*, across 12 temperatures that spanned their entire thermal breadth.

Results We found that at least 2% of all genes changed expression with temperature. The majority of upregulation was specific to exposure to low temperatures. The cool-adapted *A. picea* induced expression of more genes in response to extreme temperatures than did *A. carolinensis*, consistent with the *enhanced response* hypothesis. In contrast, under high temperatures the warm-adapted *A. carolinensis* downregulated many of the genes upregulated in *A. picea*, and required more extreme temperatures to induce down-regulation in gene expression, consistent with the *tolerance* hypothesis. We found no evidence for a trade-off between constitutive and inducible gene expression as predicted by the *genetic assimilation hypothesis*.

Conclusions These results suggest that increases in upper thermal limits may require an evolutionary shift in response mechanism away from damage repair toward tolerance and prevention.

Keywords

Aphaenogaster, gene expression, plasticity, reactionome, transcriptome

Background

Temperature regulates biological activity and shapes diversity from molecular to macroecological scales [1, 2]. Many species, especially small-bodied arthropods, live at temperatures close to their thermal limits and are at risk from current increases in temperature [3–5]. Thermal tolerance, the ability of individuals to maintain function and survive thermal extremes, depends on a complex interplay between the structural integrity of cellular components and activation of physiological response mechanisms to prevent and/or repair damage [6, 7]. Thermal defense strategies are shaped by the environmental regime organisms experience [8] and thermal limits vary considerably among species and populations [3, 4, 9, 10]. These differences in thermal tolerance are largely genetic [11, 12] with a highly polygenic basis [13–16]. Outside of candidate genes [13], little is known about the evolution of thermal tolerance or the link between short-term physiological acclimation and longer-term adaptation to novel temperature regimes. This information is critical for understanding the adaptive potential of species to future climates [17].

To address this gap of knowledge, we need information on the extent to which selection has acted upon the diversity and plasticity of genes involved in thermal tolerance [17, 18]. In recent years, whole-organism gene expression approaches (e.g. transcriptomics) using high-throughput RNA sequencing (RNAseq) technology have been widely applied to identify genes involved in thermal tolerance [19–22] and other traits. Such studies typically use an ANOVA-type experimental or sampling design, with only a few environmental levels, and often find only a few dozen to hundred genes with differential expression in different thermal regimes. However, temperature and other environmental factors vary continuously in nature. As a result, such categorical comparisons (e.g. high vs. low temperatures) are likely to miss key differences that are due not just to whether it is hot, but rather how hot it is. Continuous variation is better characterized with a reaction norm approach, which describes variation in the phenotype of a single genotype across an environmental gradient [23]. Reaction norms differ not only in mean values, but also in their shapes [10, 24], and differences in the shape of reaction norms are often larger than differences in mean values at both the species and the population level [24].

70 In this study, we extend the reaction norm approach to RNAseq analysis and introduce the *reactionome*,
71 which we define as a characterization of the reaction norm for all genes in an organism’s transcriptome
72 across an environmental gradient. Although temporal patterns of transcriptional activity (e.g. fast- vs. slow-
73 responding genes) are also important components of an organism’s transcriptional response to environmental
74 conditions [25], we focus here on the response of transcripts across conditions at the same time point.

75 We used the reactionome method to identify genes that are thermally responsive in two closely-related eastern
76 North American ant species, *Aphaenogaster carolinensis* and *A. picea* [26, 27]. *Aphaenogaster* are some of the
77 most common ants in eastern North America [28] where they are keystone seed dispersers [29–31]. Ants, and
78 ectotherms in general, have little or no thermal safety margin [5] and thus are highly susceptible to climate
79 change [4, 32], putting at risk important ecosystem services [33]. Growth chamber studies have demonstrated
80 that reproduction of *Aphaenogaster* will be compromised by increased temperatures [34], while field studies
81 [32] and simulations [35] indicate that ant species persistence will depend on combinations of physiology
82 and species interactions. *Aphaenogaster carolinensis* experiences a higher mean annual temperature (MAT)
83 (14.6°C) and less seasonal temperature variation (temperature seasonality = 7,678°) than does *A. picea* (MAT
84 = 4.6°C, seasonality = 10,008°; [36]) at their respective collection sites. In controlled laboratory experiments,
85 these warm- and cold-climate species exhibit corresponding differences in their critical maximum (44.7°C
86 for *A. carolinensis* versus 41.3°C for *A. picea*; see Methods) and minimum temperatures (6.1°C for *A.*
87 *carolinensis* versus -0.1°C for *A. picea*). These differences between species in their thermal environments and
88 physiological tolerances allowed us to investigate adaptation to both lower and upper thermal extremes in
89 this system.

90 To characterize the thermal reactionome, we measured the reaction norm for each gene using a regression-
91 based statistical approach to identify temperature-dependent patterns of change in gene expression. We used
92 these response patterns to quantitatively test three mechanistic hypotheses of thermal adaptation. First, the
93 *enhanced response hypothesis* [37–39] proposes that species extend their thermal limits through a stronger
94 induced response to provide greater protection from more frequently encountered stressors. This hypothesis
95 would predict that the cool-adapted *A. picea* would activate more genes, and induce them more strongly,
96 in response to low temperatures than would the warm-adapted *A. carolinensis*, which would show greater
97 induction in response to high temperatures.

98 Second, the *tolerance hypothesis* [9, 40] proposes that existing inducible stress responses become insufficient
99 or prohibitively costly as environmental stressors increase in frequency, resulting in a shift away from an
100 induced response in favor of structural changes [41] or behavioral adaptations [5, 42]. This hypothesis predicts
101 adaptation to stress should be associated with lower transcriptional responsiveness and less sensitivity to
102 temperature perturbation, as well as a shift to an alternate suite of tolerance genes and pathways [43,
103 44].

104 Finally, the *genetic assimilation hypothesis* [45, 46] proposes that exposure to more extreme stressors selects
105 for a shift from inducible to constitutive expression of stress-response genes. This hypothesis predicts that
106 transcripts responsive to high temperatures in *A. picea* will have higher constitutive expression in *A. caro-*
107 *linensis*, whereas transcripts responsive to low temperatures in *A. carolinensis* will have higher constitutive
108 expression in *A. picea*.

109 To summarise, in this project we generated the transcriptomes of two closely-related temperate ant species,
110 and quantified their gene expression across a wide range of thermal conditions. We then evaluated three
111 non-mutually exclusive hypotheses (enhanced response, tolerance and genetic assimilation) of the evolution
112 of thermal adaptation by comparing the number and expression patterns of transcripts between species in
113 response to extreme low and extreme high temperatures. Finally, we used gene ontology information to
114 determine which gene products and pathways are involved in thermal adaptation in the two species.

115 Results

116 Reaction norms of thermally-responsive transcripts

117 The combined *Aphaenogaster* transcriptome assembly contained 99,861 transcripts. About half of these
118 (51,246) transcripts had a significant BLAST hit, of which 50% (25,797) had a top hit to Insecta and 37%
119 (18,854) had a top hit to Formicidae. We performed a BUSCO analysis [47] to assess the quality of the
120 transcriptome assembly against the arthropod Benchmarking Universal Single-Copy Orthologs (BUSCOs).
121 This analysis revealed that transcriptome is largely complete, as we recovered 1,426 complete single-copy
122 BUSCOs (62%) and an additional 435 fragmented BUSCOs (16%), which is in line with results of Simao et
123 al. [47] for transcriptomes of other non-model species. Moreover, only 8% of the BUSCOs were found to be
124 duplicated in the transcriptome, which indicates that the steps (see Methods) we took to collapse homologs
125 in the combined transcriptome of the two species were successful.

126 We quantified gene expression using the program *Sailfish* [48], and fitted polynomial regression models
127 to the expression values of each transcript to identify those that had a linear or quadratic relationship
128 (Fig. 1). To account for multiple tests, we both applied a False Discovery Rate (FDR) correction, and
129 performed a resampling analysis to determine the number of transcripts that would be expected to have a
130 significant relationship by chance alone. We retained the 2,509 (2.5% of total) transcripts that exceeded the
131 null expectation from the resampling analysis as true positive transcripts for further analyses (Table S1). Of
132 these transcripts, 75% (1,553) had a non-linear relationship with temperature that would likely have been
133 missed with a standard differential expression experiment (e.g. high vs. low temperature). The proportion
134 of responsive transcripts is similar if we focus only on those transcript with a BLAST hit (725 significant
135 transcripts out of 51,246, 1.4). However, as with all *de novo* transcriptome assemblies, this assembly is
136 fragmented due to partial contigs and alternative transcripts [49] so this estimate is likely a lower bound for
137 the true proportion of transcripts that are thermally responsive.

138 We used the predicted transcript expression levels to partition transcripts for each species into five expression
139 categories (Fig. 1) which were defined *a priori* to allow us to test predictions derived from three thermal adap-
140 tation hypotheses of relative response severity in the two species: **High** transcripts had greatest expression
141 at temperatures $> 31^{\circ}\text{C}$, **Low** transcripts had greatest expression at temperatures $< 10^{\circ}\text{C}$, **Intermediate**
142 transcripts had greatest expression between 10 to 30°C , **Bimodal** transcripts had increased expression at
143 both high and low temperatures, while **NotResp** transcripts were those that were not thermally responsive
144 in the focal species but did respond in the other.

145 Expression response to thermal extremes differs between species

146 Although the total number of thermally-responsive transcripts did not differ between species ($\chi^2_1 = 0.08$,
147 $P = 0.77$), the two species differed in the number of transcripts in each expression category (Table 1, χ^2_4
148 $= 302.896$, $P < 0.001$). *Aphaenogaster picea* induced significantly more transcripts in response to both
149 temperature extremes (**Bimodal** transcripts in Table 1; $\chi^2_1 = 71.617$, $P < 0.001$) than did *A. carolinensis*,
150 which downregulated more transcripts under these conditions (**Intermediate** transcripts in Table 1; $\chi^2_1 =$
151 256.329 , $P < 0.001$). Consistent with the *enhanced response* hypothesis, the cool-climate *A. picea* induced
152 273 (~50%) more transcripts in response to low temperatures than the warm-climate *A. carolinensis* (**Low**
153 transcripts in Table 1; $\chi^2_1 = 71.227$, $P < 0.001$). However, there was no difference among species in the
154 number of transcripts upregulated at high temperatures (**High** transcripts in Table 1; $\chi^2_1 = 0.53$, $P =$
155 0.47).

156 In addition, we also examined the specific patterns of shifts from one expression category to another between
157 species. As transcripts may change expression between species due to neutral drift alone, we used the Stuart-
158 Maxwell test of marginal homogeneity to test if the number of responsive transcripts in each expression
159 category differed between the species when controlling for overall differences in the number of responsive
160 transcripts. We found that the expression categories of individual transcripts between the two species were
161 not randomly distributed (Stuart-Maxwell test of marginal homogeneity $\chi^2_4 = 319$, $P < 0.001$, Fig. S1).

162 Specifically, the two species differed significantly in expression pattern, which captures differences in slope
163 as well as category, for 1,553 (62%) of the thermally responsive transcripts.

164 The *enhanced response* and *tolerance* hypotheses make opposing predictions concerning the overlap in
165 response patterns between the two species (Fig. 2). The *enhanced response hypothesis* posits that temperature
166 adaptation uses existing mechanisms for thermal resistance, which should result in significant overlap in
167 response and fewer transcripts shifting expression categories than expected by chance (Fig. 2, left). In con-
168 trast, the *tolerance hypothesis* predicts that transcripts involved in active defense will become non-responsive
169 or shift to other expression categories in the better-adapted species (Fig. 2, right). We tested these predic-
170 tions by examining if the transcripts upregulated in response to the temperature extreme experienced less
171 frequently by a species (cool temperatures for the warm-climate *A. carolinensis*, and warm temperatures
172 for the cool-climate *A. picea*) displayed the same response profile in the other species that more frequently
173 experiences those conditions.

174 Transcripts upregulated at low temperatures in *A. carolinensis* (**Low** and **Bimodal** transcripts) were signif-
175 icantly biased toward this same category and away from other expression categories in *A. picea* (Fig. 3A),
176 suggesting shared response pathways as predicted by the *enhanced response* hypothesis. In contrast, tran-
177 scripts upregulated in response to high temperatures in *A. picea* (**High** and **Bimodal**) shifted expression
178 categories in *A. carolinensis* (Fig. 3B), primarily to the **Intermediate** category (Fig. 3B). These transcripts
179 are less likely to be upregulated in any context, consistent with the *tolerance hypothesis*.

180 Molecular processes suggest a generalized stress response mechanism

181 The gene set enrichment analysis revealed a number of gene groups enriched in each expression category
182 (Table S2). Across both species, there were 9 terms enriched in the **Bimodal** category, including terms
183 involved in stress response (regulation of cellular response to stress, signal transduction by p53 class media-
184 tor), cell death (apoptotic signaling pathway) and cellular organization (e.g. protein complex localization).
185 The 6 terms enriched in the **Low** category suggest that proteins undergo structural (e.g protein acylation)
186 and organizational (single-organism organelle organization) changes to tolerate colder temperatures, possibly
187 to maintain membrane fluidity [50]. The **High** category included only a single enriched GO term, “nicoti-
188 namide metabolic process”, while the **Intermediate** category had 5 terms including DNA packaging and
189 metabolic process terms.

190 *A. carolinensis* has greater inertia of expression change to increases in temper- 191 ature than does *A. picea*

192 As an additional test of the *tolerance hypothesis*, we examined the critical temperature of gene induction in
193 response to increasing and decreasing temperatures. We compared between species the mean temperatures
194 of transcript upregulation, defined as the temperature at which the transcript showed the greatest positive
195 change in expression. In support of the *enhanced response* but not the *tolerance hypothesis*, the temperature
196 of induction at low temperatures was significantly higher for the cool-climate *A. picea* than for *A. carolinensis*
197 (12.4°C) than *A. picea* (13.1°C; $t_{1308} = -3.1$, $P < 0.002$; Fig. 4A), though the temperature of induction did
198 not differ between species for high temperatures ($t_{567} = 0.8$, $P < 0.403$).

199 Similarly, for down-regulated (**Intermediate**) transcripts, we compared the mean temperatures of down-
200 regulation of transcript expression between species at both high ($> 20^\circ\text{C}$) and low ($< 20^\circ\text{C}$) temperatures.
201 Consistent with the *tolerance hypothesis*, *A. carolinensis* had greater inertia of gene expression in response
202 to increasing temperatures. The temperature of downregulation for **Intermediate** transcripts was 28.6°C
203 for *A. carolinensis* compared to 27.2 for *A. picea* ($t_{294} = 3.8$, $P < 0.001$). The difference between species
204 was not significant with decreasing temperatures ($t_{251} = 0.5$, $P = 0.584$, Fig. 4B).

205 No evidence for *genetic assimilation*

206 We tested the *genetic assimilation hypothesis* by comparing the log ratios of relative inducibility to relative
207 baseline expression at the rearing temperature (25°C). If stress-response transcripts have shifted between
208 species from inducible to constitutive expression, there should be a negative relationship between the two. We
209 found no evidence of such a relationship for either temperature extreme: transcripts more upregulated at high
210 temperatures in the cool-climate *A. picea* were not expressed at higher baseline levels in the warm-climate
211 *A. carolinensis* (Fig. 5A). Similarly, transcripts more upregulated at low temperatures in *A. carolinensis*
212 did not show higher baseline levels in *A. picea* (Fig. 5B). In fact, for both comparisons we found a weakly
213 positive relationship between relative inducibility and baseline expression between the two species ($\beta_1 = 0.31$,
214 $P < 0.001$ and ($\beta_1 = 0.21$, $P < 0.001$). In addition, the thermally responsive transcripts in *A. carolinensis*,
215 regardless of expression pattern, had higher baseline expression than those in *A. picea*, including those
216 with **Intermediate** expression profiles in both species (Wilcoxon $V = 68842$, $P < 0.001$). An important
217 exception to this pattern is the set of transcripts that had **High** or **Bimodal** expression in *A. picea* but
218 were not thermally responsive in *A. carolinensis* (top-row of Fig. 3B). These transcripts are less likely to be
219 upregulated in any context, consistent with the *tolerance hypothesis*.

220 Discussion

221 The potential for many species to persist in face of climate change will depend in part upon their thermal
222 tolerances. However, for most species little is known about how plasticity or adaptive changes in gene
223 expression underlie thermal tolerance. By using a *reactionome* approach, we were able to quantitatively
224 describe plasticity in transcript expression across a thermal gradient, and identify putative changes in gene
225 expression associated with shifts in thermal tolerance between the ant species *Aphaenogaster picea* and *A.*
226 *carolinensis*. We found non-linear patterns of gene expression changes in response to temperature, with both
227 quantitative and qualitative differences between species, consistent with different mechanisms of thermal
228 adaptation to low and high temperature extremes.

229 Under the *enhanced response* hypothesis, stress-adapted species are hypothesized to induce a stronger and
230 earlier response to extreme conditions. We found evidence for this hypothesis at low temperatures: although
231 the lower thermal limit for *A. picea* is substantially lower than *A. carolinensis*, *A. picea* upregulated responsive
232 transcripts at slightly less extreme temperatures (Fig. 4A). Moreover, the transcripts upregulated in *A. picea*
233 included about half (55%) those upregulated in *A. carolinensis* as well as an additional set of 261 transcripts
234 (Table 1), enriched for metabolism, organization and translation processes (Table S2). Two non-mutually
235 exclusive hypotheses may explain this pattern. First, surviving prolonged low temperatures, such as would
236 be experienced during overwintering, generally requires advance production of specialized cryoprotectants
237 [43] and a suite of preparatory physiological modifications [51]. The northern species *A. picea* may induce a
238 greater response to survive the longer winter period. Alternatively, the response to low temperatures may
239 reflect countergradient expression to counteract reduction in enzyme efficiency, and maintain activity as
240 temperature declines [41]. This requirement may be under stronger selection in *A. picea* given the shorter
241 growing season that would necessitate foraging under a broader range of temperatures.

242 In contrast to cold tolerance, the enhanced upper thermal limit in *A. carolinensis* is best explained by the
243 *tolerance* hypothesis. High temperatures were associated with significantly fewer upregulated transcripts in
244 *A. carolinensis* (Table 1), and a large proportion (25%) of the transcripts upregulated at high temperatures
245 in *A. picea* were either downregulated or expressed at negligible levels overall in *A. carolinensis*. These results
246 suggest that mechanisms other than the heat shock response are acting to maintain protein stability in face
247 of temperature increases. Such mechanisms may include novel constitutive defenses [19, 21, 22], enhanced
248 proteome stability [52] or behavioral quiescence [5] to tolerate thermal stress. These differences are in line
249 with expectations that *A. carolinensis*, with a growing season over twice the length of its northern congener,
250 may be better able to afford to restrain from foraging in suboptimal conditions. Indeed, quiescence under
251 stressful conditions by the red harvester ant *Pogonomyrma barbatus* has been shown to increase colony
252 fitness [42].

253 The one hypothesis that did not receive support was the *genetic assimilation hypothesis*, which predicts
254 that exposure to more frequent stressors will select for a shift from inducible to constitutive expression of
255 stress-response transcripts. This contrasts with other recent studies on adaptation in field populations to
256 thermal stress [21]. However, in a short-term selection experiment for heat tolerance, Sikkink et al. [46]
257 also found no evidence for genetic assimilation at the expression level after 10 generations of selection for
258 heat tolerance in *Caenorhabditis remanei*, even though there was a substantial increase in heat tolerance.
259 Both the genetic assimilation and tolerance routes to increasing thermal limits are functionally similar in
260 that they emphasize damage prevention rather than repair. Whether a particular taxon evolves one strategy
261 over another may be related to availability of alternative mechanisms as well as the intensity, frequency and
262 duration of temperature stress in a given environment.

263 Given the differences in the patterns of thermal responsiveness between species (Fig. 3), it is worth noting
264 a number of similarities. In both species, there were 2 – 3 times more transcripts upregulated at low
265 than high temperatures (Table 1). The degree of upregulation at low temperatures is surprising given
266 previous studies [53, 54] that found little transcriptional activity at low temperatures. However, these
267 studies exposed organisms to a few extreme ($-10 - 0^{\circ}\text{C}$) temperatures. At these extremes, we also found few
268 upregulated transcripts (Fig. 4A), whereas the peak of low-temperature transcriptional activation occurred
269 near 10°C (Fig. 4). A potential explanation for this pattern is that increased gene expression functions to
270 support elevated metabolism at moderately cold temperatures, as suggested by the metabolic cold adaptation
271 hypothesis [55]. The observation that more transcripts were upregulated at low than high temperatures
272 could also be due to stronger selection on upper than lower thermal limits, thereby reducing both genetic
273 variation and gene expression plasticity at high temperatures [4, 56]. This explanation is consistent with the
274 observation in *Aphaenogaster rudis* [57] and other ectotherms [10, 58] that critical maximum temperatures
275 vary less among taxa than do critical minimum temperatures.

276 Critical maximum and minimum temperatures are hypothesized to be genetically correlated [10, 58], but this
277 was not evident in terms of gene expression in this study. Only $\sim 10\%$ of transcripts upregulated in response to
278 temperature were bimodal, and for both activation and down-regulation, thresholds differed between species
279 at only one temperature extreme (Fig. 4). This suggests that species do not face a fundamental trade-off
280 between these two limits and may be able to shift upper and lower thermal limits independently to match
281 requirements of more seasonally variable environments. A major contribution of this study is the construction
282 of a reactionome for gene expression data. Similar approaches have been used in other species [59, 60], but to
283 our knowledge, none have applied a regression approach to identify a complete list of responsive transcript
284 across an environmental gradient. This approach revealed quantitative patterns of temperature response
285 not captured in categorical comparisons. For example, the degree of upregulation at cool ($\sim 10^{\circ}\text{C}$) but not
286 extreme cold temperatures was missed in previous studies that focused on extreme cold limits, as discussed
287 above. Further, a number of issues have hampered RNA-seq studies to date. Namely, lists of differentially
288 expressed transcripts are prone to false positives [61], depend on the genetic background of the organism
289 [62] and are prone to “storytelling” interpretations [63]. Our findings are robust to these issues as we focus
290 on the average change in the shape of the reaction norms across many hundreds of responsive transcripts
291 in each species. Although we use gene ontology information to interpret our results, the key findings about
292 differential plasticity of expression between species do not depend on functional annotation.

293 Moreover, by characterizing responses across thousands of transcripts, the reactionome approach can help
294 to distinguish selection from neutral drift in gene expression [64–66]. Although we cannot rule out drift as a
295 source of variation for individual transcripts, we would not expect to see systematic differences in expression
296 type categories or critical temperature thresholds as we do here (Fig. 3, Fig. S1). Thus, our method provides
297 an example of how focusing on transcriptome-wide changes in gene expression – as opposed to identifying lists
298 of differentially-expressed transcripts – can provide meaningful insight on the process of evolution. It should
299 be noted, however, that although including non-linear relationships between expression and temperature
300 captured a significantly larger range of biologically-relevant responses, it also led to a substantial increase in
301 false positives. Empirical estimation of these rates via randomization tests, combined with robust sampling
302 designs, can help to minimize this bias and focus results on biologically-meaningful gene sets.

303 A number of caveats do apply to our work. First, species may differ in gene expression along axes which we
304 have not measured here, especially temporal patterns of gene expression [25], which could be studied in further

305 work. Second, the *de novo* transcriptome assembly is highly fragmented, given that all sequenced ant genomes
306 to date have only about 18,000 genes [67]. Although we took steps to remove contaminants and redundant
307 transcripts, some likely remain, in addition to partially assembled transcripts. A genome assembly, in
308 progress, will help to reduce fragmentation. Third, the quality of the annotation for a non-model system such
309 as *Aphaenogaster* is not as good as it would be for model arthropods such as *Drosophila* and *Apis*. Finally,
310 the mapping of changes in gene expression to organismal fitness is far from direct [68], and large differences
311 in patterns of gene expression may have only small effects on fitness. In particular, functional protein
312 levels cannot be expected to be fully linked to mRNA abundance due to post-transcriptional modification,
313 regulation, mRNA fluctuations and protein stability [68].

314 Our results are congruent with evidence from other systems [21] that thermally-stressful habitats select
315 for investment in tolerance, whereas organisms from less stressful environments rely on plastically-induced
316 resistance. Although the heat-shock response is one of the most conserved across living organisms [39], it is
317 energetically expensive, particularly under chronic stress conditions [69]. Under such circumstances, it may
318 be advantageous to proactively prevent thermal damage even at the cost of reduced metabolic efficiency, either
319 by maintaining a higher constitutive level of chaperone proteins [11] or by increasing the thermal stability of
320 proteins at the expense of catalytic activity [70]. Thus, although in the short term increasing temperature
321 stress leads to a quantitatively stronger induced response, adapting to such stress over evolutionary time
322 appears to require a qualitative shift in mechanism of resistance that can alter not only the magnitude, but
323 the sign of gene expression change in response to temperature. Whether such a shift would be possible in
324 the compressed time frame of projected climate change, particularly for long-lived organisms such as ants,
325 is likely to be critical in determining the capacity of populations to adapt to more frequent and long-lasting
326 stressors.

327 Conclusions

328 In this work, we have brought reaction norms to the genomic era by characterizing the thermal reactionomes
329 of two temperate ant species, *Aphaenogaster picea* and *A. carolinensis*. At least 2% of their transcrip-
330 tomes are thermally responsive. Our results indicate that these two ant species have different responses to
331 thermal extremes. *A. picea* responds by increasing expression of transcripts related to metabolism, stress
332 response and other protective molecules, whereas *A. carolinensis* decreases expression of transcripts related
333 to metabolism and likely relies on other mechanisms for thermal tolerance. The thermal reactionomes of
334 these two species provide key insights into the genetic basis of thermal tolerance, and a resource for the future
335 study of ecological adaptation in ant species. Finally, the reactionome itself illustrates a new direction for
336 characterizing acclimation and adaptation in a changing climate.

337 Methods

338 Samples

339 Ants of the genus *Aphaenogaster* are some of the most abundant in eastern North America [71], and species as
340 well as populations within species differ in critical maximum and minimum temperatures [57]. Temperature
341 is a potentially strong selective force for ground-nesting ant populations, which must tolerate seasonally
342 freezing winters and hot summers. On shorter time scales, individual workers can experience extreme thermal
343 environments when they leave the thermally buffered ant nest to forage for food [32].

344 In fall 2012, we collected a single colony of *Aphaenogaster picea* from Molly Bog, Vermont (University of
345 Vermont Natural Areas; 44.508° N, -72.702° W) and a single colony of *Aphaenogaster carolinensis*, part of
346 the *A. rudis* species complex [26], from Durham, North Carolina (36.037° N -78.874° W). These sites are
347 centrally located within each species' geographic range. Along the East Coast of the United State, the distri-
348 bution of *A. picea* ranges from central Maine south to northern Pennsylvania, while *A. carolinensis* is found
349 from Pennsylvania to the Carolinas. Species identity was confirmed with morphological characters (Bernice
350 DeMarco, Michigan State University). Colonies of both species were maintained in common conditions at

351 25°C for 6 months prior to experimentation. Due to colony size limitations, we were unable to determine
352 the critical thermal limits of these particular colonies. In summer 2013 we collected additional colonies of
353 *Aphaenogaster* from Molly Bog, VT and North Carolina (Duke Forest, 36.036° N, 79.077° W). We tested the
354 upper and lower critical thermal limits for 5 ants from each of these colonies using a ramp of 1° C per minute,
355 starting at 30° C, and recorded the temperature at which the ants were no longer able to right themselves,
356 following the protocol of Warren & Chick [57].

357 Common Garden Design

358 Ideally, genetically-based variation in gene expression profiles would be identified by comparing individuals
359 completely reared under common-garden conditions to eliminate environmental variation experienced either
360 as adults or during development. However, *Aphaenogaster* colonies are long-lived, cannot be bred under
361 laboratory conditions, and do not achieve complete turnover of the workforce for at least a year or longer.
362 Thus, as is commonly done with other long-lived organisms [21, 65], we exposed both colonies to common-
363 garden rearing conditions for six months to fully acclimate adult workers to common temperatures. Over this
364 time, roughly 1-2 cohorts of new workers are expected to join each colony (~1/3 of the total), such that the
365 workers sampled for thermal traits and gene expression are likely to have included a mix of adult-acclimated
366 and fully lab-reared individuals.

367 Unlike ANOVA-based experimental designs, which derive statistical power from replication within each
368 experimental treatment level, regression designs have greater power when sampling additional values across
369 the range of the continuous predictor variable [72]. Ideally, the treatments should be replicated at each level
370 of the predictor variable [73]. However, even with no replication, the regression design is still more powerful
371 than an ANOVA design with comparable replication, and provides an unbiased estimator of the slope [72].
372 For these reasons, we focused our sequencing efforts on maximizing the number of temperatures at which
373 the transcriptome was profiled, rather than on replication at each temperature.

374 To limit differences in gene expression not related to the experimental treatment (e.g. circadian rhythm),
375 on 12 different days we haphazardly collected three ants from each 2012 colony at the same time of day
376 to minimize variation due to circadian oscillations. We measured response to temperature with a one-hour
377 static temperature application, which is ecologically relevant for workers that leave the thermally-buffered
378 nest and are immediately exposed to ambient temperatures while foraging [71]. Each day, the ants were
379 placed in glass tubes immersed in a water bath maintained at one of 12 randomly-assigned temperatures (0°
380 to 38.5°C, in 3.5° increments) for one hour. The minimum and maximum temperatures were selected based
381 on previous work showing that these temperatures are close to the critical minimum (~0°C) and maximum
382 (~43°C) temperatures for *Aphaenogaster* [57], and these treatments did not cause mortality. At the end of the
383 hour, the ants were flash frozen in liquid nitrogen and stored at -80°C. Thus, our reactionome characterized
384 early, but not late, responding genes. We extracted mRNA by homogenizing the three pooled ants in 500
385 μ L of RNazol buffer with zirconium silicate beads in a Bullet Blender (Next Advance; Averill Park, NY),
386 followed by RNazol extraction (Molecular Research Center Inc; Cincinnati, OH) and then an RNeasy micro
387 extraction (Qiagen Inc; Valencia, CA) following the manufacturer's instructions.

388 Sequencing, assembly and annotation

389 For each species, the 12 samples were barcoded and sequenced in a single lane of 2 x 100bp paired-end
390 reads on an Illumina HiSeq 1500 yielding 200 and 160 million reads for the *A. picea* and *A. carolinensis*
391 samples respectively. Reads were filtered to remove Illumina adapter sequences and low quality bases using
392 the program Trimmomatic [74].

393 We assembled the sequenced reads into the full set of mRNA transcripts, the transcriptome, for the com-
394 bined data set from both species using the Trinity *de novo* transcriptome assembly program [75]. *De novo*
395 transcriptome assembly is prone to falsely identifying alternative transcripts and identifying inaccurate tran-
396 scripts that are chimeric (e.g. regions of two separate transcripts that assemble into a false, or chimeric, third
397 transcript) [76]. We removed potentially false transcripts by first running the program CAP3 [77] to cluster

398 sequences with greater than 90% similarity and merge transcripts with overlaps longer than 100 bp and 98%
399 similar in length. Second, we ran the program `uclust` which clusters sequences completely contained within
400 longer sequences at greater than 90% similarity (see Supplementary Methods). We used liberal values (90%
401 similarity) to merge orthologous transcripts in the two species that may not have assembled together in the
402 initial *de novo* transcriptome assembly. To identify contaminant sequences, we screened our full transcrip-
403 tome using the program `DeconSeq` [78] with the provided bacteria, virus, archaen and human databases of
404 contaminants.

405 The Trinity *de novo* transcriptome assembly for both species assembled together included 126,172 transcripts
406 with a total length of 100 million bp. Filtering to remove redundant or chimeric reads resulted in an assembly
407 with 105,536 transcripts. The total length was 63 million bp with an N_{50} length of 895 bp and a mean
408 transcript size of 593 bp. Of the 105,536 filtered transcripts, 55,432 had hits to the NCBI-nr database. Of
409 these, 38,711 transcripts mapped to GO terms, 1,659 transcripts were identified to an enzyme and 18,935
410 transcripts mapped to a domain with >50% coverage. We removed 5,675 transcripts identified as known
411 contaminants, leaving 99,861 clean transcripts.

412 We assessed the quality of the transcriptome assembly using the BUSCO program [47] available from (<http://busco.ezlab.org/>). BUSCO assesses transcriptome completeness by measuring the number of near-universal
413 single-copy orthologs selected from OrthoDB, using the Arthropod database.
414

415 To determine the putative function of the transcripts, we used functional annotation of the transcriptome
416 assembly using the web-based tool `FastAnnotator` [79] which annotates and classifies transcripts by Gene
417 Ontology (GO) term assignment, enzyme identification and domain identification.

418 Identification of thermally-responsive transcripts

419 We quantified expression of each transcript using the program `Sailfish` [48] and used the bias-corrected
420 transcripts per million (TPM) [80] as our measure of transcript expression. We included the contaminant
421 transcripts identified by `DeconSeq` at the quantification stage to avoid incorrectly assigning reads to other
422 transcripts, but removed these from further analyses. Because preliminary examination of the data (Sup-
423plementary Methods) indicated that the 7°C samples may have been mis-labeled, we omitted these data
424 from the analysis. The expression values were highly correlated between species at each temperature treat-
425ment ($r^2 > 0.98$) indicating that assembling the transcriptome with data from both species was justified
426 (Supplementary Methods).

427 To identify transcripts that had significant changes in expression across the thermal gradient, we fit to each
428 transcript an ordinary least-squares polynomial regression model

$$\log(TPM+1) = \beta_0 + \beta_1(\text{species}) + \beta_2(\text{temperature}) + \beta_3(\text{temperature}^2) + \beta_4(\text{species} * \text{temperature}) + \beta_5(\text{species} * \text{temperature}^2)$$

429 Temperature and species were both fixed effects, with a quadratic term included for temperature. We used
430 $\log(TPM + 1)$ as the response to control for skew in the expression data. For a continuous predictor such
431 as temperature, this regression approach is preferred to an ANOVA approach as it can reveal non-linear
432 responses such as hump-shaped or threshold effects [72]. This method is robust to over-dispersion because
433 we expect errors in the read count distribution [81] to be independent with respect to temperature.

434 To evaluate the statistical significance of the patterns, we computed parametric *P*-values for each model
435 and adjusted these *P*-values using the False Discovery Rate (FDR) approach of Benjamini and Hochberg
436 [82]. As a more stringent filter for false positives, we then randomly re-assigned each transcript within
437 a species to a different temperature, fit the polynomial models as above, and again calculated *P*-values
438 and FDR. Ideally, these randomized data sets should not yield any significant associations. We repeated
439 this resampling approach 100 times, and used the 95th quantile of false significant transcripts as the null
440 expectation for retaining transcripts from the true data.

441 Of these overall significant transcripts, we identified thermally-responsive transcripts as the subset that
442 had significant $\beta_2(\text{temp})$, $\beta_3(\text{temp}^2)$, $\beta_4(\text{species} * \text{temp})$ or $\beta_5(\text{species} * \text{temp}^2)$ terms after step-wise model

443 selection by AIC. For each thermally-responsive transcript, we predicted expression levels using the final
444 linear model for each species across the tested thermal range. We used the predicted transcript expression
445 levels to partition transcripts for each species into the five *a priori* defined expression categories: **High**
446 transcripts had greatest expression at temperatures $> 31^{\circ}\text{C}$, **Low** transcripts had greatest expression at
447 temperatures $< 10^{\circ}\text{C}$, **Intermediate** transcripts had greatest expression between 10 to 30°C , **Bimodal**
448 transcripts had increased expression at both high and low temperatures, while **NotResp** transcripts were
449 those that were not thermally responsive in the focal species but did respond in the other. For the **Bimodal**
450 group, we required that expression at both low and high temperatures was at least one standard deviation
451 greater than the expression at the rearing temperature of 25°C . Because expression category was defined
452 by the temperature of maximal expression, both **Low** and **High** categories were biased toward transcripts
453 up-regulated at that temperature extreme, but also likely included some transcripts down-regulated at the
454 opposing extreme. The two categories which could unambiguously distinguish up- from down-regulation are
455 *Bimodal* (up at both extremes) and *Intermediate* (down at both extremes).

456 Statistical analyses

457 We used χ^2 tests to determine if the total number of responsive transcripts, and the number of transcripts
458 in each expression category differed between species. To evaluate if shifts from one expression category to
459 another between the two species were randomly distributed, we used the Stuart-Maxwell test of marginal
460 homogeneity from the `coin` package [83] in R [84] which tests if the row and column marginal proportions
461 are in equity.

462 To test whether the temperature at which thermally-responsive transcripts were activated differs between
463 species, we identified the temperature at which there was the greatest change in expression for each tran-
464 script in each species, using only the transcripts with a significant species x temperature interaction. For
465 upregulated transcripts, we grouped the **High** transcripts along with the high temperature end of the **Bi-**
466 **modal** transcripts, and did the same for **Low** transcripts. We then performed a *t*-test to determine if the
467 mean temperature of transcript activation differed between the two species for each group. For downregu-
468 lated transcripts (i.e. **Intermediate**), we identified the greatest change in expression for each transcript in
469 response to both increasing ($> 20^{\circ}\text{C}$) and decreasing ($< 20^{\circ}\text{C}$) temperatures, and used a *t*-test to compare
470 the mean temperature of down-regulation between species.

471 To test for a tradeoff between inducibility and constitutive baseline expression between species, we fit ordinary
472 least squares regressions with the log ratio of relative constitutive expression as the response variable and
473 the log ratio of relative inducibility as the predictor variable for **High** transcripts in *A. picea* and for **Low**
474 transcripts in *A. carolinensis*. Constitutive expression was defined as predicted expression at 25°C , whereas
475 inducibility of each transcript was defined as $((\text{maximum TPM} - \text{minimum TPM}) / \text{minimum TPM}) \times 100$.
476 In addition, we used a Mann-Whitney test to compare the baseline constitutive expression between species
477 for all responsive transcripts.

478 Gene set enrichment analysis

479 To describe the molecular processes involved in thermal adaptation, we performed gene set enrichment
480 analysis (GSEA) using the `parentChild` algorithm [85] from the package `topGO` [86] in R [84]. Briefly, this
481 approach identifies GO terms that are overrepresented in the significant transcripts relative to all GO terms
482 in the transcriptome, after accounting for dependencies among the GO terms.

483 All analyses were performed with R 3.2 [84] and are fully reproducible (Supplementary Methods).

484 Availability of supporting data

485 Table S1 provides the annotation, *P*-value, r^2 , adjusted *P*-value, and expression type for the thermally-
486 responsive transcripts in each species.

487 Table S2 provides the results of the gene set enrichment analysis, showing the enriched gene ontology terms
488 for each species in each thermal response category.

489 The Supplementary Methods contain the detailed information on the analysis. The reproducible and version-
490 controlled scripts underlying the analysis are available on GitHub ([https://github.com/johnstantongeddes/
491 ApTranscriptome](https://github.com/johnstantongeddes/ApTranscriptome)).

492 The Illumina short-read sequence data supporting the results of this article are available in the NCBI
493 Short Read Archive BioProject repository, PRJNA260626 [http://www.ncbi.nlm.nih.gov/bioproject/
494 PRJNA260626/](http://www.ncbi.nlm.nih.gov/bioproject/PRJNA260626/).

495 The Trinity transcriptome assembly, FastAnnotator annotation file and Sailfish gene expression quantification
496 files supporting the results of this article are available from the LTER data portal, datasets hf113-38, hf113-
497 41, and hf113-42 (<http://dx.doi.org/10.6073/pasta/05ea6464df30efa2f1e2c7439366bf47>).

498 Competing interests

499 The authors declare they have no competing interests.

500 Authors' contributions

501 JSG, NG and SHC designed research. JSG, ADN and LC performed research. JSG, JV, MV and SCH
502 analyzed data and wrote the paper. ADN and LC performed research. JV and MV analyzed data. JSG,
503 RD, AE, NS, NG and SHC wrote the paper. All authors read and approved of the final manuscript.

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508 and do not necessarily represent the official views of NIGMS or NIH.

509 Figure Legends

510 **Figure 1.** Illustration of the patterns against temperature for each of the four expression categories, **Bi-**
511 **modal, High, Intermediate** and **Low**. The fifth category of **Not Responsive** is not shown.

512 **Figure 2.** Illustrations of the expected thermal response patterns in the two species under alternative
513 mechanistic hypotheses of temperature adaptation. Although both temperature extremes were investigated
514 in a similar way, for simplicity only the response to low temperatures is illustrated here. Each column
515 indicates the distribution across all response categories in *A. picea*, which has a lower CT_{min} and is therefore
516 better adapted to low temperatures, for the set of transcripts identified as cold-induced (either **High** or
517 **Bimodal** categories) in the species with higher CT_{min} , *A. carolinensis*, relative to the null hypothesis of
518 equal marginal frequencies. The dashed boxes highlight cells that would indicate matched responses in the
519 two species, and the color of each cell (blue = excess, orange = deficit) represents the deviation of the
520 observed from expected number of transcripts. The (A) *enhanced response* hypothesis proposes that the
521 increase in cold tolerance in *A. picea* is achieved by amplifying existing molecular mechanisms, and thus
522 there should be an excess of shared response types between species. In contrast, the (B) *tolerance hypothesis*
523 predicts that *A. picea* is less reliant on induced responses to confer cold-tolerance than *A. carolinensis*,
524 leading to an excess of shifts from induction in *A. carolinensis* to the **Not Responsive** or down-regulation
525 categories in *A. picea*.

526 **Figure 3.** Results of analysis of thermal response patterns in the two species. The color of each cell (blue
527 = excess, orange = deficit) represents the deviation of the observed from the expected number of transcripts
528 based on hypothetical equivalence of the marginal frequencies. The units are number of transcripts. For
529 each temperature extreme, the species expected to be less well adapted to that extreme is displayed on
530 the x-axis for the two response categories corresponding to upregulation (**Bimodal** and **Low** for the low
531 temperatures, or **Bimodal** and **High** for high temperatures). The distribution of response categories for
532 those transcripts in the better-adapted species is arrayed along the y-axis. The dashed boxes indicate the
533 matched responses (e.g. **High - High**). (A) Low temperature extreme: there is an excess of shared **Low**
534 and **Bimodal** expression types and a bias away from all other categories in *A. picea*, consistent with the
535 *enhanced response* hypothesis (Fig. 2). (B) High temperature extreme: in addition to an excess of matched
536 categories, there is an excess of **High** and **Bimodal** transcripts in *A. picea* that are not upregulated in *A.*
537 *carolinensis* (**Intermediate** and **Not Responsive**), partially consistent with the *tolerance* hypothesis. The
538 complete set of matched observations is shown in Fig. S1. Expression types are defined in Table 1.

539 **Figure 4.** Histogram with smooth density estimate of temperature of maximum rate of change in expres-
540 sion for transcripts that have (A) increased expression at **Low** and **High** temperatures and (B) decreased
541 expression at **Low** and **High** temperatures. Red bars and lines are for *A. carolinensis* while blue bars and
542 lines are for *A. picea*.

543 **Figure 5.** Scatterplots of log ratios of relative inducibility to relative constitutive expression, defined as
544 expression level at the common rearing temperature (25°C) for (A) **High** transcripts in *A. picea* ($P < 0.001$,
545 $r^2 = 0.07$) and (B) **Low** transcripts in *A. carolinensis* ($P < 0.001$, $r^2 = 0.1$). Blue lines and confidence
546 intervals are from ordinary least squares regressions.

547 **Figure S1.** Deviations from expected numbers of transcripts in matched observations of transcript expres-
548 sion type between species (*A. carolinensis* on rows, *A. picea* on columns). The color of each cell represents
549 the deviation of the observed from the expected number of transcripts based on hypothetical equivalence of
550 the marginal frequencies (blue = excess, orange = deficit). The expression types are **Low** transcripts that
551 had greatest expression temperatures $< 10^\circ\text{C}$, **Intermediate** transcripts with greatest expression between
552 10 and 30°C , **High** transcripts that had greatest expression at temperatures $> 31^\circ$, **Bimodal** transcripts
553 with increased expression at both high and low temperatures, and **Not Responsive** transcripts that were
554 not thermally responsive in that species.

Table 1: Table of the number of thermally-responsive transcripts by expression type for *A. carolinensis* and *A. picea*. **Low** are transcripts with increased expression at low temperatures ($< 10^{\circ}\text{C}$), **Intermediate** are transcripts with maximum expression between $10 - 30^{\circ}\text{C}$, **High** are transcripts with increased expression at high temperatures ($> 31^{\circ}\text{C}$), **Bimodal** are transcripts with increased expression at both low and high temperatures, while **NotResp** are transcripts that are not thermally responsive in one species but are in the other species.

	Low	Intermediate	High	Bimodal	NotResp
A. picea	1,193	249	248	278	110
A. carolinensis	920	680	232	117	129

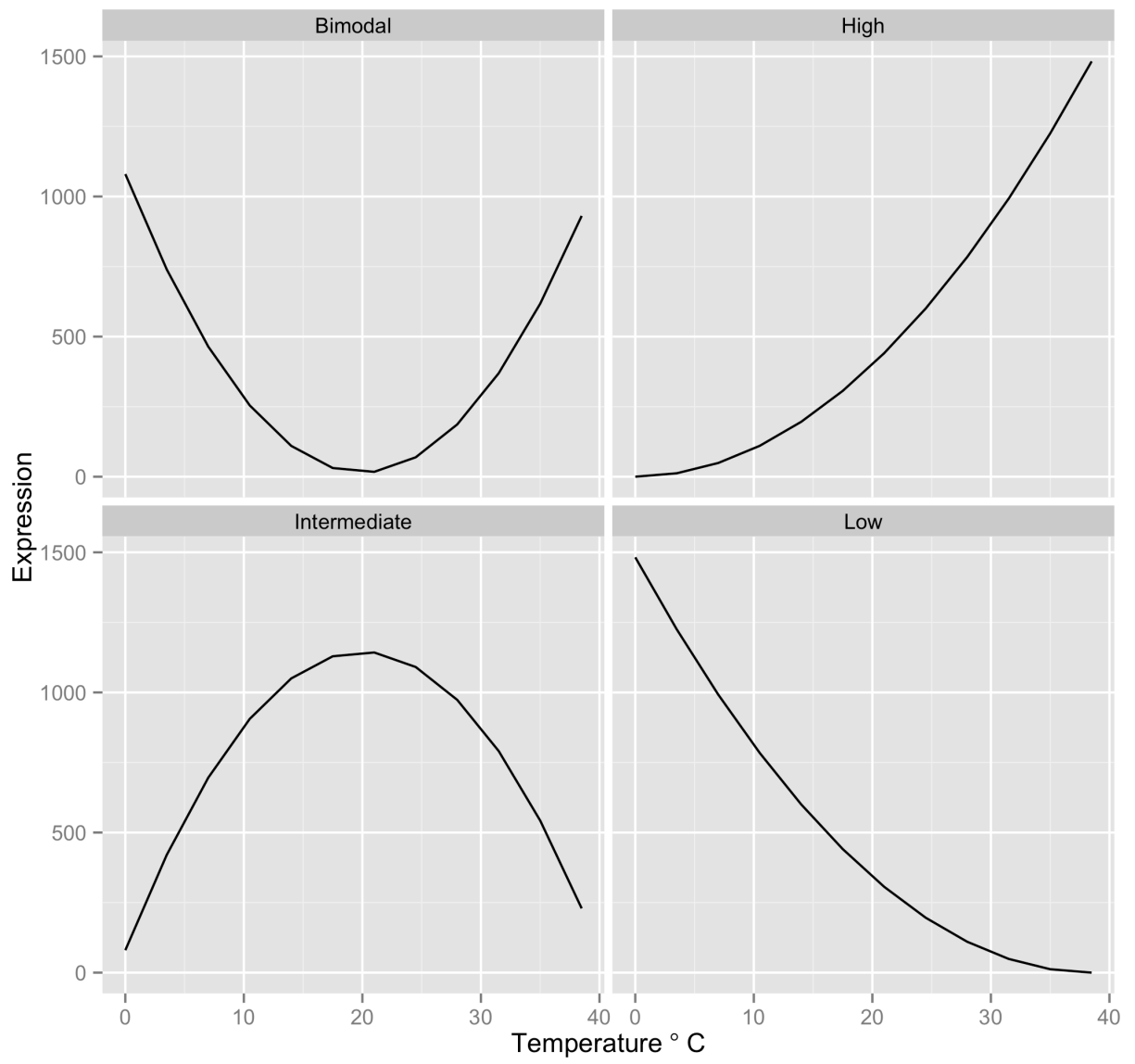


Figure 1: Fig. 1

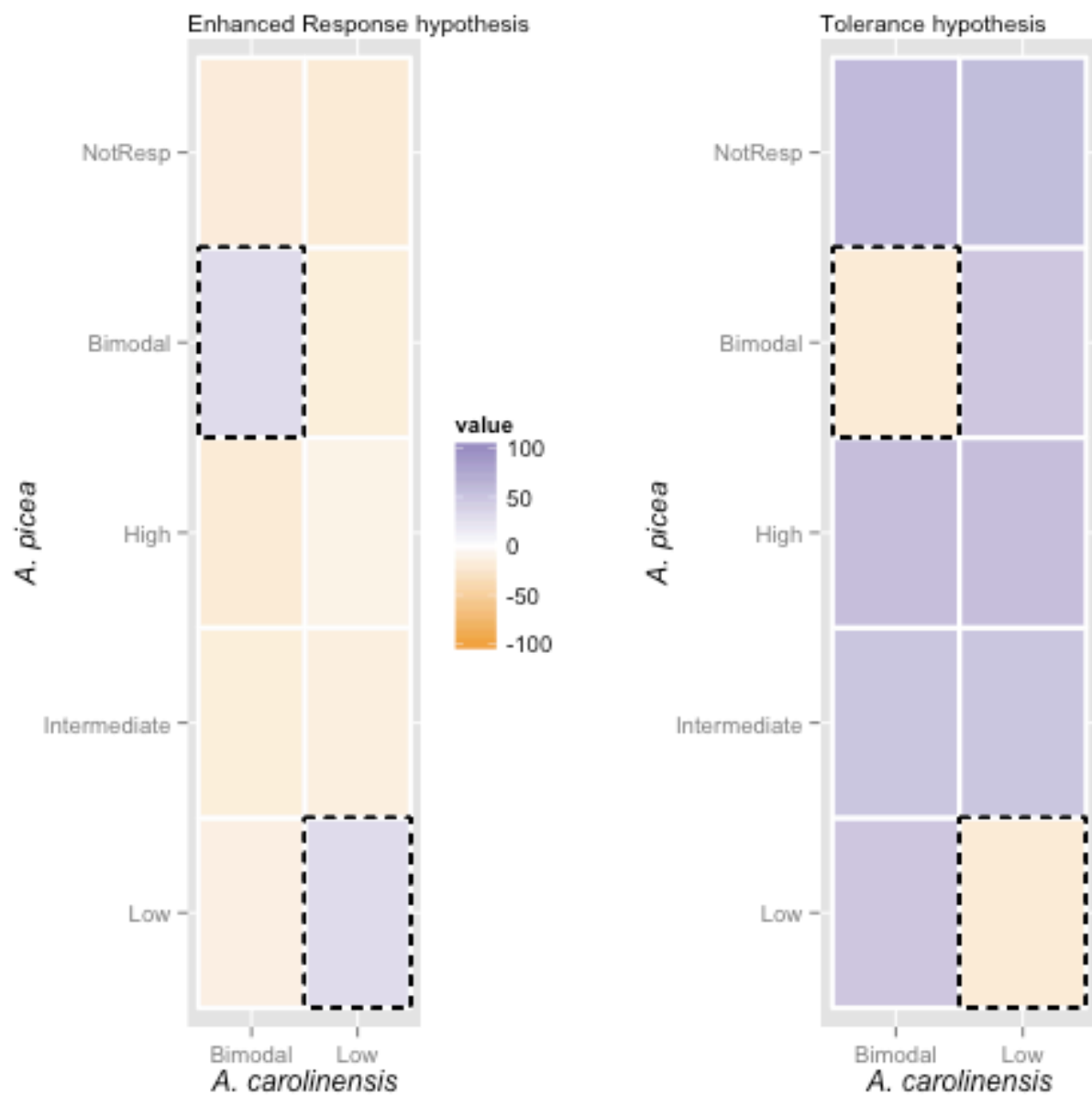


Figure 2: Fig. 2

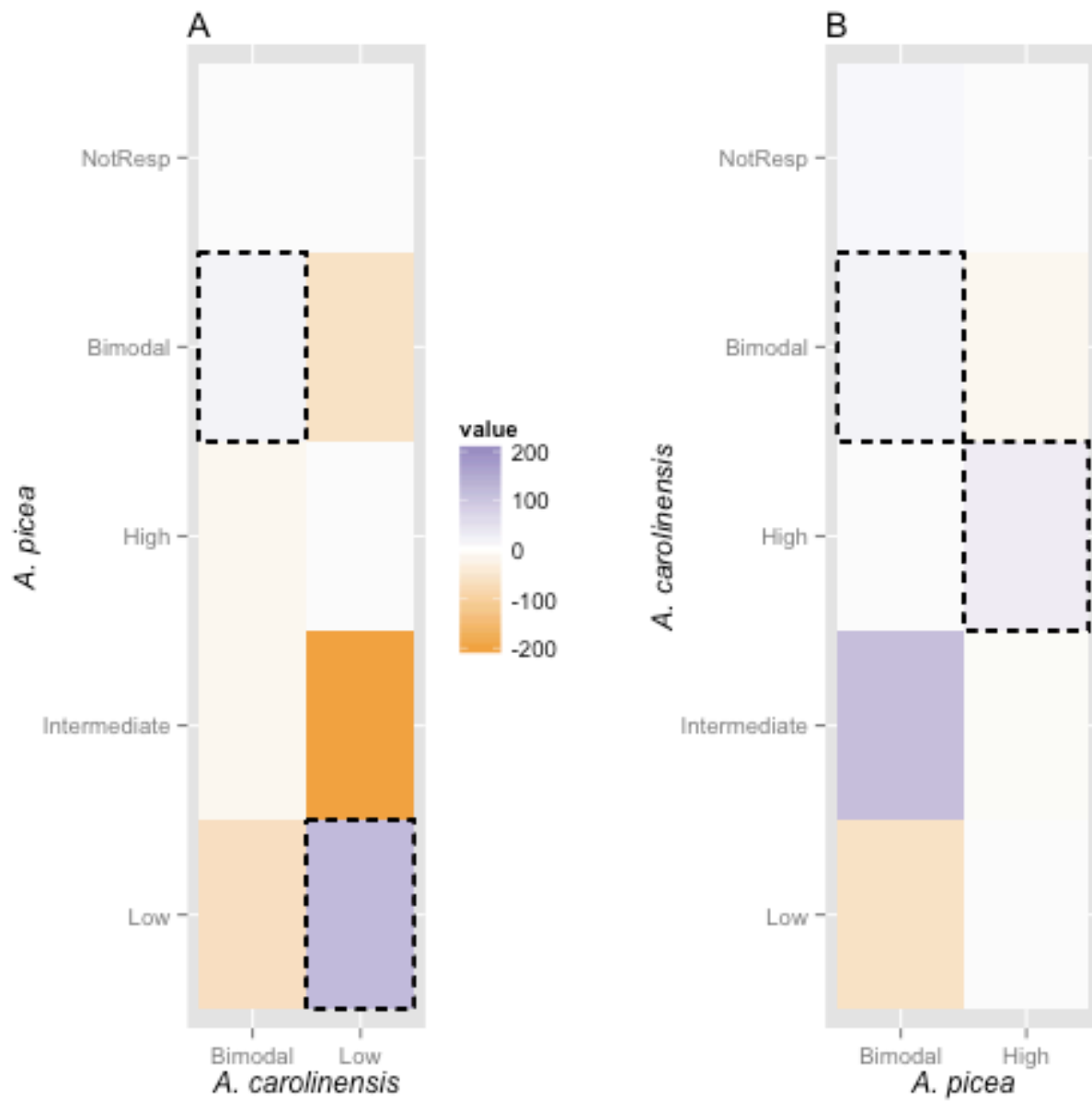


Figure 3: Fig. 3

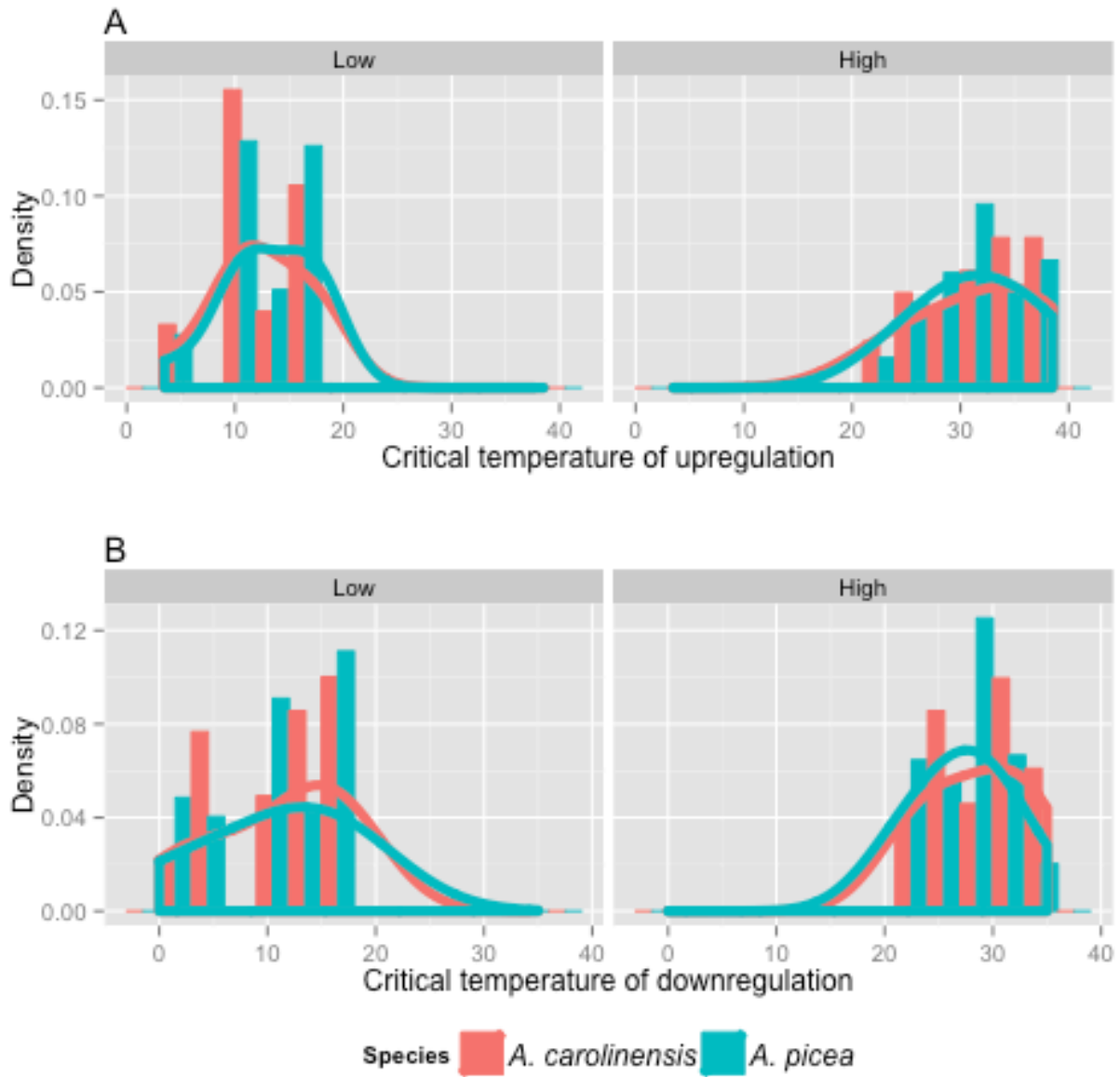


Figure 4: Fig. 4

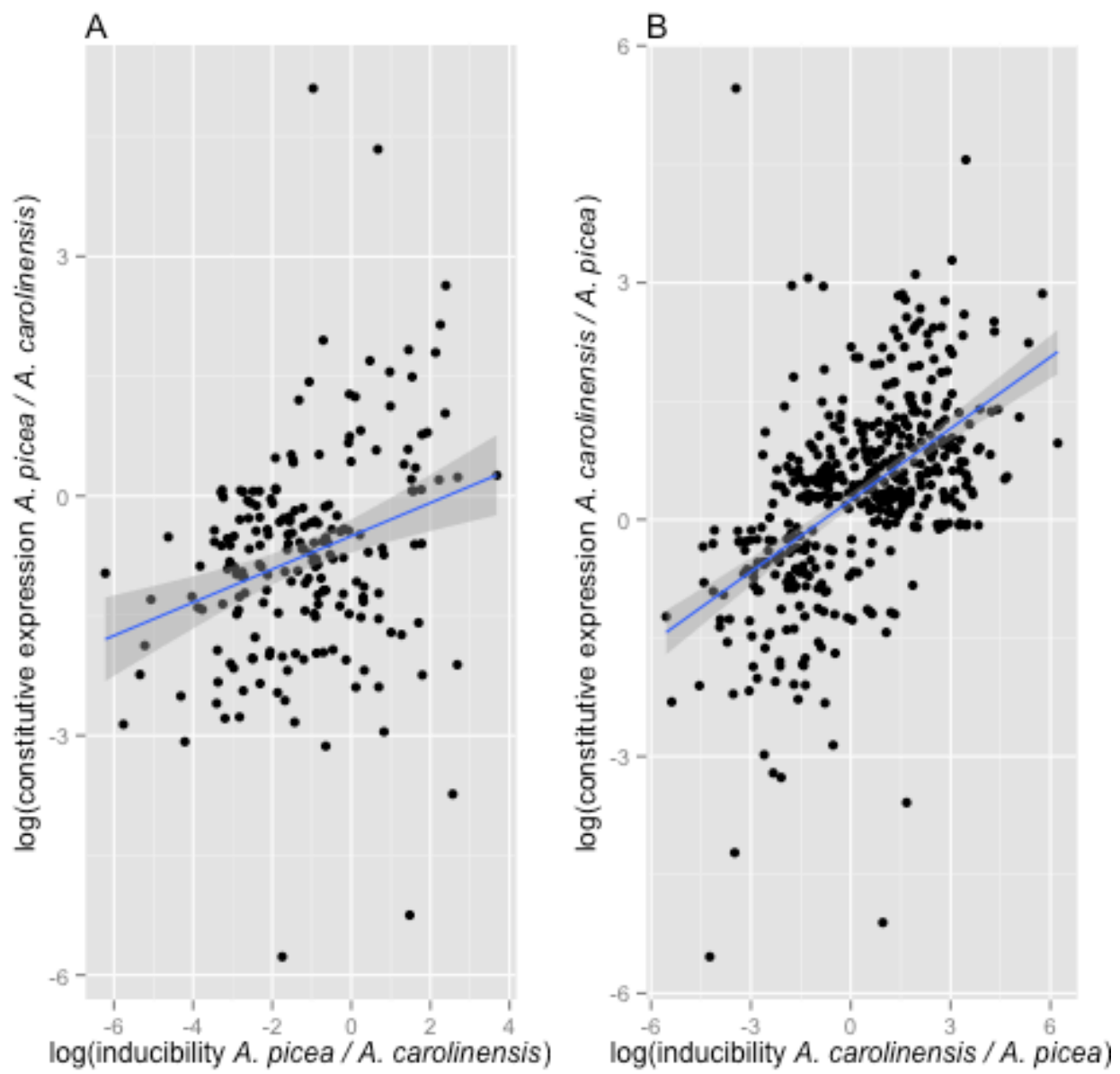


Figure 5: Fig. 5

References

- 557 1. Brown JH, Gillooly JF, Allen AP, Savage VM, West GB: **Toward a metabolic theory of ecology.**
558 *Ecology* 2004, **85**:1771–1789.
- 559 2. Kingsolver JG: **The well-temperated biologist.** *American Naturalist* 2009, **174**:755–768.
- 560 3. Deutsch CA, Tewksbury JJ, Huey RB, Sheldon KS, Ghalambor CK, Haak DC, Martin PR: **Impacts of**
561 **climate warming on terrestrial ectotherms across latitude.** *Proceedings of the National Academy of*
562 *Sciences* 2008, **105**:6668–6672.
- 563 4. Kingsolver JG, Diamond SE, Buckley LB: **Heat stress and the fitness consequences of climate**
564 **change for terrestrial ectotherms.** *Functional Ecology* 2013, **27**:1415–1423.
- 565 5. Sunday JM, Bates AE, Kearney MR, Colwell RK, Dulvy NK, Longino JT, Huey RB: **Thermal-safety**
566 **margins and the necessity of thermoregulatory behavior across latitude and elevation.** *Proceed-*
567 *ings of the National Academy of Sciences* 2014:201316145.
- 568 6. Huey RB, Kingsolver JG: **Evolution of thermal sensitivity of ectotherm performance.** *Trends in*
569 *Ecology & Evolution* 1989, **4**:131–135.
- 570 7. Richter K, Haslbeck M, Buchner J: **The heat shock response: Life on the verge of death.** *Molecular*
571 *Cell* 2010, **40**:253–266.
- 572 8. Angilletta MJ, Wilson RS, Navas CA, James RS: **Tradeoffs and the evolution of thermal reaction**
573 **norms.** *Trends in Ecology & Evolution* 2003, **18**:234–240.
- 574 9. Cowles RB: **Possible implications of reptilian thermal tolerance.** *Science* 1939, **90**:465–466.
- 575 10. Hoffmann AA, Chown SL, Clusella-Trullas S: **Upper thermal limits in terrestrial ectotherms:**
576 **How constrained are they?** *Functional Ecology* 2013, **27**:934–949.
- 577 11. Krebs R, Loeschcke V: **Estimating heritability in a threshold trait: Heat-shock tolerance in**
578 ***drosophila buzzatii*.** *Heredity* 1997, **79**:252–259.
- 579 12. Kellermann V, Overgaard J, Hoffmann AA, Fløjgaard C, Svenning J-C, Loeschcke V: **Upper thermal**
580 **limits of *drosophila* are linked to species distributions and strongly constrained phylogenet-**
581 **ically.** *Proceedings of the National Academy of Sciences* 2012, **109**:16228–16233.
- 582 13. Krebs RA, Feder ME, Lee J: **Heritability of expression of the 70KD heat-shock protein in**
583 ***drosophila melanogaster* and its relevance to the evolution of thermotolerance.** *Evolution* 1998,
584 **52**:841–847.
- 585 14. Williams BR, Van Heerwaarden B, Dowling DK, Sgrò CM: **A multivariate test of evolutionary**
586 **constraints for thermal tolerance in *drosophila melanogaster*.** *Journal of Evolutionary Biology*
587 2012, **25**:1415–1426.
- 588 15. Morgan TJ, Mackay TFC: **Quantitative trait loci for thermotolerance phenotypes in *drosophila***
589 ***melanogaster*.** *Heredity* 2006, **96**:232–242.
- 590 16. Takahashi KH, Okada Y, Teramura K: **Genome-wide deficiency screen for the genomic regions**
591 **responsible for heat resistance in *drosophila melanogaster*.** *BMC Genetics* 2011, **12**:57.
- 592 17. Hoffmann AA, Willi Y: **Detecting genetic responses to environmental change.** *Nature Reviews*
593 *Genetics* 2008, **9**:421–432.
- 594 18. Somero GN: **Comparative physiology: A “crystal ball” for predicting consequences of global**
595 **change.** *American Journal of Physiology - Regulatory, Integrative and Comparative Physiology* 2011,
596 **301**:R1–R14.
- 597 19. Meyer E, Aglyamova GV, Matz MV: **Profiling gene expression responses of coral larvae (*acropora***
598 ***millepora*) to elevated temperature and settlement inducers using a novel RNA-seq procedure.**
599 *Molecular Ecology* 2011, **20**:3599–616.

- 600 20. Teets NM, Peyton JT, Colinet H, Renault D, Kelley JL, Kawarasaki Y, Lee RE, Denlinger DL: **Gene**
601 **expression changes governing extreme dehydration tolerance in an antarctic insect.** *Proceedings*
602 *of the National Academy of Sciences* 2012, **109**:20744–9.
- 603 21. Barshis DJ, Ladner JT, Oliver TA, Seneca FO, Traylor-Knowles N, Palumbi SR: **Genomic basis for**
604 **coral resilience to climate change.** *Proceedings of the National Academy of Sciences* 2013, **110**:1387–
605 1392.
- 606 22. O’Neil ST, Dzurisin JDK, Williams CM, Lobo NF, Higgins JK, Deines JM, Carmichael RD, Zeng E,
607 Tan JC, Wu GC, Emrich SJ, Hellmann JJ: **Gene expression in closely related species mirrors local**
608 **adaptation: Consequences for responses to a warming world.** *Molecular Ecology* 2014, **23**:2686–
609 2698.
- 610 23. Gomulkiewicz R, Kirkpatrick M: **Quantitative genetics and the evolution of reaction norms.**
611 *Evolution* 1992, **46**:390–411.
- 612 24. Murren CJ, Maclean HJ, Diamond SE, Steiner UK, Heskell MA, Handelsman CA, Ghalambor CK, Auld
613 JR, Callahan HS, Pfennig DW, Relyea RA, Schlichting Carl D., Kingsolver J: **Evolutionary change in**
614 **continuous reaction norms.** *The American Naturalist* 2014, **183**:453–467.
- 615 25. Sørensen JG, Nielsen MM, Kruhøffer M, Justesen J, Loeschcke V: **Full genome gene expression**
616 **analysis of the heat stress response in *drosophila melanogaster*.** *Cell Stress & Chaperones* 2005,
617 **10**:312–328.
- 618 26. Umphrey G: **Morphometric discrimination among sibling species in the *fulva - rudis - texana***
619 **complex of the ant genus *aphaenogaster*.** *Canadian Journal of Zoology* 1996, **74**:528–559.
- 620 27. DeMarco B, Cognato A: **A multiple-gene phylogeny reveals polyphyly among eastern north**
621 **american *aphaenogaster* species.** *Zoologica* 2015, doi:10.1111/zsc.12168.
- 622 28. King JR, Warren RJ, Bradford MA: **Social insects dominate eastern US temperate hardwood**
623 **forest macroinvertebrate communities in warmer regions.** *PLoS ONE* 2013, **8**:e75843.
- 624 29. Ness JH, Morin DF, Giladi I: **Uncommon specialization in a mutualism between a temperate**
625 **herbaceous plant guild and an ant: Are *aphaenogaster* ants keystone mutualists?** *Oikos* 2009,
626 **118**:1793–1804.
- 627 30. Zelikova TJ, Sanders NJ, Dunn RR: **The mixed effects of experimental ant removal on seedling**
628 **distribution, belowground invertebrates, and soil nutrients.** *Ecosphere* 2011, **2**:art63.
- 629 31. Rodriguez-Cabal MA, Stuble KL, Guénard B, Dunn RR, Sanders NJ: **Disruption of ant-seed disper-**
630 **sal mutualisms by the invasive asian needle ant (*pachycondyla chinensis*).** *Biological Invasions*
631 2012, **14**:557–565.
- 632 32. Diamond SE, Nichols LM, McCoy N, Hirsch C, Pelini SL, Sanders NJ, Ellison AM, Gotelli NJ, Dunn
633 RR: **A physiological trait-based approach to predicting the responses of species to experimental**
634 **climate warming.** *Ecology* 2012, **93**:2305–2312.
- 635 33. Toro ID, Ribbons RR, Pelini SL: **The little things that run the world revisited: A review of**
636 **ant-mediated ecosystem services and disservices (hymenoptera: Formicidae).** *Myrmecological*
637 *News* 2012, **17**:133–146.
- 638 34. Pelini SL, Diamond SE, Maclean HJ, Ellison AM, Gotelli NJ, Sanders NJ, Dunn RR: **Common garden**
639 **experiments reveal uncommon responses across temperatures, locations, and species of ants.**
640 *Ecology and Evolution* 2012, **2**:3009–15.
- 641 35. Sharon B, Stuble KL, Lessard J-P, Dunn RR, Adler FR, Sanders NJ: **Predicting future coexistence**
642 **in a north american ant community.** *Ecology and Evolution* 2014, **4**:1804–1819.
- 643 36. Hijmans R, Cameron S, Parra J, Jones P, Jarvis A: **Very high resolution interpolated climate**
644 **surfaces of global land areas.** *International Journal of Climatology* 2005, **25**:1965–1978.

- 645 37. Hofmann GE, Somero GN: **Interspecific variation in thermal denaturation of proteins in the**
646 **congeneric mussels *mytilus trossulus* and *m. galloprovincialis*: Evidence from the heat-shock**
647 **response and protein ubiquitination.** *Marine Biology* 1996, **126**:65–75.
- 648 38. Feder ME, Hofmann GE: **Heat-shock proteins, molecular chaperones, and the stress response:**
649 **Evolutionary and ecological physiology.** *Annual Review of Physiology* 1999, **61**:243–282.
- 650 39. Kültz D: **Molecular and evolutionary basis of the cellular stress response.** *Annual Review of*
651 *Physiology* 2005, **67**:225–257.
- 652 40. Fields PA: **Protein function at thermal extremes: Balancing stability and flexibility.** *Compar-*
653 *ative Biochemistry and Physiology Part A: Molecular & Integrative Physiology* 2001, **129**:417–431.
- 654 41. Lockwood BL, Somero GN: **Functional determinants of temperature adaptation in enzymes of**
655 **cold- versus warm-adapted mussels (genus *mytilus*).** *Molecular Biology and Evolution* 2012, **29**:3061–
656 3070.
- 657 42. Gordon DM: **The rewards of restraint in the collective regulation of foraging by harvester**
658 **ant colonies.** *Nature* 2013, **498**:91–93.
- 659 43. Neelakanta G, Hudson AM, Sultana H, Cooley L, Fikrig E: **Expression of *ixodes scapularis* an-**
660 **tifreeze glycoprotein enhances cold tolerance in *drosophila melanogaster*.** *PLoS ONE* 2012,
661 **7**:e33447.
- 662 44. Franssen SU, Bergmann N, Winters G, Klostermeier UC, Rosenstiel P, Bornberg-Bauer E, Reusch
663 TBH: **Transcriptomic resilience to global warming in the seagrass *zostera marina*, a marine**
664 **foundation species.** *Proceedings of the National Academy of Sciences* 2011, **108**:19276–19281.
- 665 45. Waddington C: **Genetic assimilation of an acquired character.** *Evolution* 1953, **7**:118–126.
- 666 46. Sikkink KL, Reynolds RM, Ituarte CM, Cresko WA, Phillips PC: **Rapid evolution of phenotypic**
667 **plasticity and shifting thresholds of genetic assimilation in the nematode *Caenorhabditis***
668 ***remanei*.** *G3: Genes Genomes Genetics* 2014, **4**:1103–1112.
- 669 47. Simao FA, Waterhouse RM, Ioannidis P, Kriventseva EV: **BUSCO: Assessing genome assembly**
670 **and annotation completeness with single-copy orthologs.** *Bioinformatics* 2015, **10.1093/bioinfor-**
671 **matics/btv351.**
- 672 48. Patro R, Mount SM, Kingsford C: **Sailfish enables alignment-free isoform quantification from**
673 **RNA-seq reads using lightweight algorithms.** *Nature Biotechnology* 2014, **32**:462–464.
- 674 49. Vijay N, Poelstra JW, Künstner A, Wolf JBW: **Challenges and strategies in transcriptome as-**
675 **sembly and differential gene expression quantification. a comprehensive in silico assessment**
676 **of RNA-seq experiments.** *Molecular Ecology* 2013, **22**:620–634.
- 677 50. Ohtsu T, Kimura MT, Katagiri C: **How *drosophila* species acquire cold tolerance.** *Eur J Biochem*
678 1998, **252**:608–611.
- 679 51. Denlinger DL: **Regulation of diapause.** *Annual Review of Entomology* 2002, **47**:93–122.
- 680 52. Ghosh K, Dill K: **Cellular proteomes have broad distributions of protein stability.** *Biophysical*
681 *Journal* 2010, **99**:3996–4002.
- 682 53. Teets NM, Peyton JT, Ragland GJ, Colinet H, Renault D, Hahn DA, Denlinger DL: **Combined**
683 **transcriptomic and metabolomic approach uncovers molecular mechanisms of cold tolerance**
684 **in a temperate flesh fly.** *Physiological Genomics* 2012, **44**:764–777.
- 685 54. Vesala L, Salminen T, Laiho A, Hoikkala A, Kankare M: **Cold tolerance and cold-induced mod-**
686 **ulation of gene expression in two *drosophila virilis* group species with different distributions:**
687 **Cold-induced changes in gene expression.** *Insect Molecular Biology* 2012, **21**:107–118.
- 688 55. Addo-Bediako A, Chown SL, Gaston KJ: **Metabolic cold adaptation in insects: A large-scale**
689 **perspective.** *Functional Ecology* 2002, **16**:332–338.

- 690 56. Kelly MW, Grosberg Richard K., Sanford E: **Trade-offs, geography, and limits to thermal adap-**
691 **tation in a tide pool copepod.** *The American Naturalist* 2013, **181**:846–854.
- 692 57. Warren RJ, Chick L: **Upward ant distribution shift corresponds with minimum, not maximum,**
693 **temperature tolerance.** *Global Change Biology* 2013, **19**:2082–2088.
- 694 58. Addo-Bediako A, Chown SL, Gaston KJ: **Thermal tolerance, climatic variability and latitude.**
695 *Proceedings of The Royal Society B: Biological Sciences* 2000, **267**:739–745.
- 696 59. Hodgins-Davis A, Adomas AB, Warringer J, Townsend JP: **Abundant gene-by-environment inter-**
697 **actions in gene expression reaction norms to copper within *saccharomyces cerevisiae*.** *Genome*
698 *Biology and Evolution* 2012, **4**:1061–1079.
- 699 60. Aubin-Horth N, Renn SCP: **Genomic reaction norms: Using integrative biology to understand**
700 **molecular mechanisms of phenotypic plasticity.** *Molecular Ecology* 2009, **18**:3763–3780.
- 701 61. González E, Joly S: **Impact of RNA-seq attributes on false positive rates in differential**
702 **expression analysis of de novo assembled transcriptomes.** *BMC Research Notes* 2013, **6**:503.
- 703 62. Sarup P, Sørensen JG, Kristensen TN, Hoffmann AA, Loeschcke V, Paige KN, Sørensen P: **Candidate**
704 **genes detected in transcriptome studies are strongly dependent on genetic background.** *PLoS*
705 *ONE* 2011, **6**:e15644.
- 706 63. Pavlidis P, Jensen JD, Stephan W, Stamatakis A: **A critical assessment of storytelling: Gene on-**
707 **tology categories and the importance of validating genomic scans.** *Molecular Biology and Evolution*
708 2012, **29**:3237–3248.
- 709 64. Khaitovich P, Weiss G, Lachmann M, Hellmann I, Enard W, Muetzel B, Wirkner U, Ansorge W, Pääbo
710 S: **A neutral model of transcriptome evolution.** *PLoS Biology* 2004, **2**:E132.
- 711 65. Whitehead A, Crawford DL: **Neutral and adaptive variation in gene expression.** *Proceedings of*
712 *the National Academy of Sciences* 2006, **103**:5425–5430.
- 713 66. Ogasawara O, Okubo K: **On theoretical models of gene expression evolution with random**
714 **genetic drift and natural selection.** *PLoS ONE* 2009, **4**:e7943.
- 715 67. Gadau J, Helmkampf M, Nygaard S, Roux J, Simola DF, Smith CR, Suen G, Wurm Y, Smith CD: **The**
716 **genomic impact of 100 million years of social evolution in seven ant species.** *Trends in Genetics*
717 2012, **28**:14–21.
- 718 68. Feder ME, Walser J-C: **The biological limitations of transcriptomics in elucidating stress and**
719 **stress responses.** *Journal of Evolutionary Biology* 2005, **18**:901–910.
- 720 69. Hoekstra LA, Montooth KL: **Inducing extra copies of the hsp70 gene in *drosophila melanogaster***
721 **increases energetic demand.** *BMC Evolutionary Biology* 2013, **13**:1–11.
- 722 70. Arnold FH, Wintrode PL, Miyazaki K, Gershenson A: **How enzymes adapt: Lessons from directed**
723 **evolution.** *Trends in Biochemical Sciences* 2001, **26**:100–106.
- 724 71. Lubertazzi D: **The biology and natural history of *aphaenogaster rudis*.** *Psyche: A Journal of*
725 *Entomology* 2012, **2012**:1–11.
- 726 72. Gotelli NJ, Ellison AM: *A Primer of Ecological Statistics*. 2nd edition. Sunderland, MA: Sinauer
727 Associates, Inc; 2012.
- 728 73. Cottingham KL, Lennon JT, Brown BL: **Knowing when to draw the line: Designing more**
729 **informative ecological experiments.** *Frontiers in Ecology and the Environment* 2005, **3**:145–152.
- 730 74. Lohse M, Bolger AM, Nagel A, Fernie AR, Lunn JE, Stitt M, Usadel B: **RobiNA: A user-friendly,**
731 **integrated software solution for RNA-seq-based transcriptomics.** *Nucleic Acids Research* 2012,
732 **40**:W622–W627.
- 733 75. Grabherr MG, Haas BJ, Yassour M, Levin JZ, Thompson D a, Amit I, Adiconis X, Fan L, Raychowdhury
734 R, Zeng Q, Chen Z, Mauceli E, Hacohen N, Gnirke A, Rhind N, Palma F di, Birren BW, Nusbaum C,

- 735 Lindblad-Toh K, Friedman N, Regev A: **Full-length transcriptome assembly from RNA-seq data**
736 **without a reference genome.** *Nature Biotechnology* 2011, **29**:644–52.
- 737 76. Yang Y, Smith SA: **Optimizing de novo assembly of short-read RNA-seq data for phyloge-**
738 **nomics.** *BMC Genomics* 2013, **14**:328.
- 739 77. Huang X, Madan A: **CAP3: A DNA sequence assembly program.** *Genome Research* 1999,
740 **9**:868–877.
- 741 78. Schmieder R, Edwards R: **Fast identification and removal of sequence contamination from**
742 **genomic and metagenomic datasets.** *PLoS ONE* 2011, **6**:e17288.
- 743 79. Chen T-W, Gan R-CR, Wu TH, Huang P-J, Lee C-Y, Chen Y-YM, Chen C-C, Tang P: **FastAnnotator-**
744 **an efficient transcript annotation web tool.** *BMC Genomics* 2012, **13**(Suppl 7):S9.
- 745 80. Wagner GP, Kin K, Lynch VJ: **Measurement of mRNA abundance using RNA-seq data: RPKM**
746 **measure is inconsistent among samples.** *Theory in Biosciences* 2012, **131**:281–285.
- 747 81. Anders S, Huber W: **Differential expression analysis for sequence count data.** *Genome Biology*
748 2010, **11**:R106.
- 749 82. Benjamini Y, Hochberg Y: **Controlling the false discovery rate: A practical and powerful**
750 **approach to multiple testing.** *Journal of the Royal Statistical Society Series B (Methodological)* 1995,
751 **57**:289–300.
- 752 83. Hothorn T, Hornik K, Mark van de Wiel, Zeileis A: **Implementing a class of permutation tests:**
753 **The coin package.** *Journal of Statistical Software* 2008, **28**:1–23.
- 754 84. R Core Team: **R: A language and environment for statistical computing.** 2013.
- 755 85. Grossmann S, Bauer S, Robinson PN, Vingron M: **Improved detection of overrepresentation of**
756 **gene-ontology annotations with parent–child analysis.** *Bioinformatics* 2007, **23**:3024–3031.
- 757 86. Alexa A, Rahnenführer J, Lengauer T: **Improved scoring of functional groups from gene expres-**
758 **sion data by decorrelating GO graph structure.** *Bioinformatics* 2006, **22**:1600–1607.