

1 **Exploring the universal ecological responses to climate change in a univoltine**  
2 **butterfly**

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**Running title:** Temperature effects on body size, phenology, and geographic range

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## 26 **Summary**

- 27       **1.** Animals with distinct life stages are often exposed to different temperatures  
28           during each stage. Thus, how temperature affects these life stages should be  
29           considered for broadly understanding the ecological consequences of climate  
30           warming on such species. For example, temperature variation during particular  
31           life stages may affect respective change in body size, phenology, and  
32           geographic range, which have been identified as the “universal” ecological  
33           responses to climate change. While each of these responses has been  
34           separately documented across a number of species, it is not known whether  
35           each response occurs together within a species. The influence of temperature  
36           during particular life stages may help explain each of these ecological  
37           responses to climate change.
- 38       **2.** Our goal was to determine if monthly temperature variation during particular  
39           life stages of a butterfly species can predict respective changes in body size  
40           and phenology. We also refer to the literature to assess if temperature  
41           variability during the adult stage influences range change over time.
- 42       **3.** Using historical museum collections paired with monthly temperature records,  
43           we show that changes in body size and phenology of the univoltine butterfly,  
44           *Hesperia comma*, are partly dependent upon temporal variation in summer  
45           temperatures during key stages of their life cycle. June temperatures, which  
46           are likely to affect growth rate of the final larval instar, are important for  
47           predicting adult body size (for males only; showing a positive relationship  
48           with temperature). July temperatures, which are likely to influence the pupal  
49           stage, are important for predicting the timing of adult emergence (showing a

50 negative relationship with temperature). Previous studies show that August  
51 temperatures, which act on the adult stage, are linked to range change.

52 **4.** Our study highlights the importance of considering temperature variation  
53 during each life stage over historic time-scales for understanding intraspecific  
54 response to climate change. Range edge studies of ectothermic species that  
55 have annual life cycles, long time-series occurrence data, and associated  
56 temperature records (ideally at monthly resolutions), could be useful model  
57 systems for intraspecific tests of the universal ecological responses to climate  
58 change and for exploring interactive effects.

59

60 **Key-words:** body size, climate change, global warming, *Hesperia comma*,  
61 Lepidoptera, museum collections, phenology, range change, Silver-spotted Skipper,  
62 temperature variation

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64 **Introduction**

65

66 Ecologists are increasingly reporting responses to climate change that appear to be  
67 ubiquitous across taxa and habitat types. Notably, some studies suggest that warming  
68 may be causing widespread body size declines (Gardner *et al.* 2011; Sheridan &  
69 Bickford 2011) while others show that many aquatic and terrestrial species are  
70 experiencing earlier phenological events and range expansions (Walther *et al.* 2002;  
71 Parmesan & Yohe 2003; Hickling *et al.* 2006; Miller-Rushing & Primack 2008;  
72 Diamond *et al.* 2011). Collectively, these are thought to be the three “universal”  
73 ecological responses to climate change (Daufresne, Lengfellner & Sommer 2009;  
74 Ohlberger 2013). Yet if such universal responses indeed exist, then each of these  
75 responses should be observable within and between species and at varying temporal  
76 scales (i.e. not just recently). At the century scale for example, one could hypothesize  
77 that years with warm temperatures could result in a species (i) reducing its body size,  
78 (ii) emerging, flowering, or spawning earlier (or other phenological events), and (iii)  
79 expanding its range. Yet despite empirical support for each response interspecifically  
80 across some groups, it is not known whether each response may occur within a  
81 species. Intraspecific tests of each response are important, in part, because responses  
82 to warming are likely to be interactive, which may be easier to explain at the  
83 intraspecific scale. For example, body size is thought to influence dispersal ability  
84 (linked to range expansion) and the timing of phenological events within species  
85 (Ozgul *et al.* 2010; McCauley & Mabry 2011). Moreover, organisms with complex  
86 life cycles experience different temperatures during each life stage. How different life  
87 stages separately and collectively respond to temperature is essential for  
88 understanding intraspecific response to climate change (Kingsolver *et al.* 2011;

89 Buckley *et al.* 2015), including changes in body size, phenology, and geographic  
90 range.

91

92 Species that complete their life cycles in one year (such as univoltine insects) may be  
93 useful for testing intraspecific response to temperature change; particularly if studied  
94 populations are near a range edge, where they may be approaching the limits of their  
95 thermal tolerance. For some such species, it may be possible to link temperature  
96 variation of particular months during key life stages to respective changes in body  
97 size, phenology, and probability of range change. In holometabolous insects, for  
98 example, adult body size is a direct result of growth rate during the larval stages  
99 (Shingleton 2011). Thus, if temperature is a factor influencing larval growth rate, then  
100 temperatures during the particular month(s) of the larval phase are likely to be  
101 important for predicting adult body size. Temperature should be especially important  
102 during the final larval instar, which is a critical period when holometabolous insects  
103 attain the critical size needed to initiate metamorphosis (Shingleton 2011). Similarly,  
104 the timing of phenological events and range changes may be partly dependent upon  
105 respective temperatures during the subsequent pupal and adult stages of  
106 holometabolous insects (see below).

107

108 Though rarely discussed in tandem, the timing of phenological events and range  
109 changes have often been linked to temperature variability across multiple taxa and  
110 habitat types using time-series data (see first paragraph references), but these trends  
111 have not generally been examined alongside temporal analyses of temperature-size  
112 responses. There is a particular need for such studies using invertebrates given that  
113 they represent the majority of animal biodiversity, live in all habitat types, are of

114 fundamental ecological importance, and perhaps most importantly, they are  
115 exclusively ectothermic; thus, they are highly sensitive to changes in temperature  
116 (Bickford, Sheridan & Howard 2011; Ohlberger 2013). Until recently, the prevailing  
117 hypothesis was that adult body sizes of invertebrates will get smaller with increasing  
118 temperature (Sheridan & Bickford 2011), but the direction of the temperature-size  
119 response may depend upon a number of factors, such as habitat, food quality, sexual  
120 size dimorphism, season length, voltinism, and others (Diamond & Kingsolver 2010;  
121 Stillwell *et al.* 2010; Forster, Hirst & Atkinson 2012; Ghosh, Testa & Shingleton  
122 2013; Horne, Hirst & Atkinson 2015).

123

124 A recent meta-analysis of intraspecific temperature-size responses of arthropods  
125 under laboratory conditions and across latitude revealed an interesting dichotomy of  
126 response between multivoltine (more than two broods or generations per year) and  
127 univoltine (one brood or generation per year) terrestrial species (Horne, Hirst &  
128 Atkinson 2015). Multivoltine species tend to get smaller with increasing temperature  
129 and at lower latitudes, whereas univoltine species show the opposite response,  
130 suggesting that univoltine arthropods exhibit a converse Bergmann cline (Horne, Hirst  
131 & Atkinson 2015). These differences are thought to be due to evolutionary  
132 adaptations to variation in season length such that univoltine species take advantage  
133 of a longer growing season (i.e. at lower latitudes and/or higher temperatures) by  
134 growing larger, whereas multivoltine species may use a longer growing season by  
135 maturing earlier at smaller sizes to produce more generations per year (Horne, Hirst &  
136 Atkinson 2015). However, the studies used for the meta-analysis were restricted to  
137 laboratory and spatial comparisons, it is therefore unknown if the body sizes of  
138 univoltine species respond to variations in seasonal temperature from year to year.

139 Specifically, do the adults of univoltine species within the same region reach larger  
140 sizes in years with warm temperatures during the final larval instar stage (i.e. an  
141 effectively longer growing season) compared to relatively cool years?

142

143 A key step for testing intraspecific ecological responses to temperature change is the  
144 establishment of a historical baseline of trends, at the highest feasible spatial and  
145 temporal resolution, before the recent (1970s onwards) onset of rapid climate  
146 warming. This requires copious amounts of historical data (such as body size and  
147 phenological records) to be paired with historic temperature records (ideally at  
148 monthly or daily resolutions). Natural history collections, which often consist of  
149 thousands of specimens with detailed information on collection date and locality, can  
150 provide invaluable datasets for such studies (Johnson *et al.* 2011). In Britain, for  
151 example, both monthly temperature data and natural history collections of butterfly  
152 specimens, dating back over a century, are available. When paired, Brooks *et al.*  
153 (2014) showed that a number of British butterfly adults emerge earlier (using  
154 specimen collection date as a proxy for emergence date) during years with warm  
155 spring temperatures and later in cool, wet springs. Likewise, Kharouba *et al.* (2014)  
156 found that the timing of flight season of Canadian butterflies was related to spring  
157 temperatures (also using museum collections), but the strength of response varied  
158 according to taxon specific ecological traits (i.e. species with shorter flight seasons  
159 and shorter wingspan were more sensitive). Unlike adult body size change in  
160 holometabolous insects, where it is hypothesized that temperature during the final  
161 instar larval stage will be an important predictor, phenological responses (in this case,  
162 adult emergence from the pupa) are more likely to be dependent upon temperature  
163 just before adults emerge, during the pupal stage.

164  
165 Predictors of range change, on the other hand, should be partly dependent on  
166 temperature during the adult phase of the life cycle of winged holometabolous insects,  
167 when individuals are reproductive and capable of longer dispersal. For example, years  
168 with warm August temperatures have been linked with high local abundances and  
169 range expansion of the univoltine Silver-spotted Skipper (*Hesperia comma*, Linnaeus,  
170 1758) in southeastern England since the early 1980s (see Davies *et al.* 2005; Davies *et*  
171 *al.* 2006 for full descriptions of recent range dynamics). Alternatively, years with  
172 comparatively cool August temperatures have reduced populations and are expected  
173 to contribute to range contractions/local extinctions (Lawson *et al.* 2012; Lawson *et*  
174 *al.* 2013). Alongside improved habitat management, the range expansion of *H. comma*  
175 is thought largely to be a result of increased availability of thermally suitable habitat  
176 due to recent climate warming (Thomas *et al.* 2001; Davies *et al.* 2006; Lawson *et al.*  
177 2012). Specifically, egg-laying rates are temperature dependent and females adjust  
178 oviposition based on the relative temperature of the larval foodplant (the grass -  
179 *Festuca ovina*; Davies *et al.* 2006). Warm August temperatures are correlated with  
180 higher egg-laying rates and the number of microhabitats available for optimal  
181 oviposition (Thomas *et al.* 2001; Davies *et al.* 2006). Interestingly, the recently  
182 expanded portions of the *H. comma* range are generally comprised of individuals with  
183 larger relative investment in body size (as measured by relative thorax size),  
184 suggesting that larger individuals are capable of longer distance dispersal (Hill,  
185 Thomas & Lewis 1999).  
186  
187 Given the apparent sensitivity of *H. comma* population sizes and range dynamics to  
188 August temperature variation, one may expect that body size and phenology would

189 also be highly sensitive to temperature in this species, particularly for monthly  
190 temperatures prior to August when individuals are either in the larval or pupal stage.  
191 As such, we hypothesize that (i) years with warm temperatures during the final larval  
192 instar stage (June) will lead to larger adults and (ii) years with warm months during  
193 the pupal stage (July) will lead to earlier adult emergence (phenology). We use wing  
194 length measurements (as a proxy for body size) and collection date (as a proxy for  
195 adult emergence date) of digitized Natural History Museum (NHM, London)  
196 specimens paired with historic monthly temperature records to test these hypotheses.

197

198

## 199 **Materials and methods**

200

### 201 TEMPERATURE RECORDS

202

203 Mean monthly air temperature data are available from two sources: the central  
204 England temperature records (CET; <http://www.metoffice.gov.uk/hadobs/hadcet/>) and  
205 regional monthly records from the UK MET Office  
206 (<http://www.metoffice.gov.uk/climate/uk/summaries/datasets>). The CET covers a  
207 region triangulated by Lancashire, London, and Bristol and dates from 1659 (Manley  
208 1974; Parker, Legg & Folland 1992; Perry & Hollis 2005). For central England, mean  
209 monthly minimum and maximum temperature data are available from 1878 (Parker &  
210 Horton 2005) and monthly precipitation data from 1873 (Alexander & Jones 2001).  
211 However, this area is slightly outside most of the southern England chalk grasslands  
212 range of *H. comma*. Alternatively, monthly records for the England southeast and  
213 central south region encompasses the modern range of *H. comma*, yet are only  
214 available from 1910 onwards. Previous researchers have shown that CET data are

215 representative of the UK as a whole (Croxton *et al.* 2006), and paired monthly  
216 correlations between the regional and CET data for the years between 1910-1981  
217 (encompassing the overlap in CET and regional temperature data for all years of  
218 NHM specimen collection) justify this conclusion (all Pearson's correlations > 0.96).  
219 In addition, pairwise comparisons of mean monthly air temperatures between the two  
220 record types are not significantly different (Wilcoxon signed-rank test;  $p > 0.05$ )  
221 except for August temperatures ( $p = 0.02$ ) where the regional data are warmer than  
222 CET data by  $0.42^{\circ}\text{C}$  on average. Although August air temperature records are slightly  
223 warmer in the regional dataset, this is the month when the vast majority of *H. comma*  
224 individuals are adults, and are thus past the growth and emergence stages of their life  
225 cycle (the focus of our analysis). Given the broad similarity between CET and  
226 regional monthly temperature records, we have chosen to focus our analysis using the  
227 CET data since it covers the entire temporal range of collected specimens useful for  
228 body size and phenology analyses (1880-1973; see below).

229

## 230 STUDY SYSTEM

231

232 *Hesperia comma* adults spend much of their time basking or feeding on a variety of  
233 nectar sources while staying inactive during overcast days. The species' life cycle is  
234 one generation per year (univoltine) and it is one of the last butterflies to emerge as an  
235 adult in southern England. Individuals generally spend September to March in the  
236 ovum stage, mid to late March through June as larvae (the final instar occurs in June)  
237 and approximately one month as a pupa (~July). Their life cycle culminates with the  
238 adult flight period from late July to early September (UK Butterfly Monitoring  
239 Scheme). The vast majority of field counts of adults of this species are recorded in  
240 August (Lawson *et al.* 2013). Like other British butterflies, *H. comma* has been well

241 collected by amateur and professional naturalists, particularly from the mid-19<sup>th</sup>  
242 century through the 1960s (Brooks *et al.* 2014). The NHM houses a very large  
243 collection of British butterflies (65 species) comprising ~180,000 specimens, which  
244 have been digitized, geo-referenced, and databased. 863 of these specimens are *H.*  
245 *comma*, collected from 1860-1981, about half of which are useful for body size and/or  
246 phenology analysis (see below). As with abundance counts in the field, the vast  
247 majority of specimens were collected in August (84%). Importantly, the NHM data  
248 are restricted to counties within southern England (particularly southeast England:  
249 >50% of specimens are from Hertfordshire, Surrey, Kent, and Dorset), thus keeping  
250 the geographic scope of the study comparable to modern field studies (e.g. Davies *et*  
251 *al.* 2006; Lawson *et al.* 2012; Lawson *et al.* 2013).

252

## 253 WING LENGTH DATA

254

255 Forewing length was chosen as a proxy for body size (the point of wing attachment on  
256 the thorax to the apex of each forewing; Fig. 1) using digitized NHM specimens and  
257 Image-J software. We chose forewing length as opposed to other metrics of body size  
258 (i.e. body length) because it is less prone to shrinkage over time due to specimen  
259 drying. To confirm that forewing length scales with another potential metric of body  
260 size, we correlated forewing surface area by forewing length for a subset of  
261 specimens (n=43). The correlation is very high ( $r = 0.97$ ), supporting the use of  
262 forewing length as a proxy for overall wing size, and by extension, body size.

263

264 Because we are interested in the relationship between monthly temperature variation  
265 and wing length, we only measured the forewing lengths of specimens that were field  
266 caught and labeled with a collection month. We averaged the measurements of left

267 and right forewing lengths for each specimen with relatively un-damaged wings. For  
268 each sex, we calculated the median value of our wing length measurements across  
269 specimens per year for years that contain three or more specimens.

270

271 We have focused our wing-size analysis and discussion based on specimens collected  
272 in August as they represent the overwhelming majority of specimens (see above) and  
273 August coincides with the peak period of adult abundance (UK Butterfly Monitoring  
274 Scheme). However, including specimens collected in June (2% of specimens), July  
275 (11% of specimens), or September (3% of specimens) did not qualitatively change our  
276 results (see below). As a result, the wing length dataset of August collected  
277 individuals consists of 331 specimens collected from 58 years from 1880 to 1973. 158  
278 of these specimens are female, collected over 30 years from 1880-1971. 173  
279 specimens are male, collected over 28 years from 1892-1973. These data were paired  
280 with the associated monthly mean, minimum, and maximum CET temperature values  
281 for each year, and total monthly precipitation for each year (mm).

282

### 283 WING LENGTH ANALYSIS

284

285 We performed a multiple linear regression analysis to model the relationship between  
286 forewing length and nine variables: mean monthly temperatures from March through  
287 September (i.e. the months spanning the larval, pupal, and adult life stages), year of  
288 collection, and sex as a factor variable (after confirming that assumptions for running  
289 a linear model are met). Variable selection for final models was performed using  
290 stepwise regression in both directions using the MASS package in R (Venables &  
291 Ripley 2002). Variance inflation factors (VIF) were determined using the car package  
292 (Fox & Weisberg 2011). We repeated the above analyses using minimum and

293 maximum monthly temperatures and total monthly precipitation (mm) as predictors of  
294 wing-length.

295

296 We repeated the analysis using an information-theoretic (IT) approach. Models were  
297 selected using (IT) model selection, with model averaging based on Akaike  
298 Information Criterion (AIC) to linearly relate wing length to the explanatory variables  
299 listed above (following Burnham & Anderson 2002). We applied the *dredge* function  
300 of the R package *MuMIn* (Barton 2013) to fit models for all possible combinations of  
301 explanatory variables and then ranked them based on AICc. We then extracted the  
302 model-averaged coefficient for each variable that was present in at least one candidate  
303 model. The set of candidate models was defined as those with  $\Delta AIC \leq 7$  (Burnham,  
304 Anderson & Huyvaert 2011). We identified the importance of each variable based on  
305 its frequency in the candidate models. An importance score of 1.0 indicates that a  
306 variable was present in all candidate models. The importance scores and the model-  
307 averaged coefficients were used to determine the main variables for explaining wing  
308 length. Specifically, if a variable had an importance score of 1.0 and did not have a  
309 coefficient (slope) estimate that included zero, then we were confident that it is a main  
310 variable for explaining wing length (or collection date, see below). We further  
311 identified the most important variables by determining which are retained after nested  
312 models were removed (Richards, Whittingham & Stephens 2011) using the nested  
313 function in *MuMIn* (Barton 2013). The removal of nested models reduces the chance  
314 of selecting overly complex models (i.e. those that include variables which add little  
315 or no predictive power) while not affecting the selection of the very best models  
316 (Richards, Whittingham & Stephens 2011). In practice, variables with the highest  
317 importance scores are the best predictors and will be retained regardless of whether

318 nested models are removed. For presentation purposes, we show the importance  
319 scores and coefficient estimates for all variables (calculated from the nested and un-  
320 nested candidate models) while highlighting which variables are retained when nested  
321 models are removed (Tables 1-3 and SI tables 1-15).

322

323

324 PHENOLOGY DATA

325

326 For phenological analysis, we included records in the analysis only if i) the data labels  
327 specified the location of collection to at least vice-county level (see Fig. S1 for a map  
328 of collection locations), ii) the day of collection was recorded and iii) if the specimens  
329 were field caught. Dates that varied by more than three standard deviations from the  
330 mean collection date were treated as outliers and excluded from further analysis, as  
331 were specimens with unreliable locality data (i.e. locations remote from the known  
332 20<sup>th</sup> century distribution). Collection dates were converted to day number after  
333 December 31<sup>st</sup>. The median and 10<sup>th</sup> percentile collection dates were calculated for  
334 each year in which there were five or more records.

335

336 PHENOLOGY ANALYSIS

337

338 Following the methods outlined above for wing-length, we performed a multiple  
339 linear regression analysis using stepwise regression to examine the relationship  
340 between 10<sup>th</sup> percentile and median collection dates with the explanatory variables of  
341 mean monthly temperature (March through September) and year of collection. We  
342 repeated analyses using minimum and maximum monthly temperatures and total

343 monthly precipitation (mm). Further, we used IT-AIC model selection as described  
344 above to relate collection dates to the explanatory variables.

345

## 346 **Results**

347

### 348 WING LENGTH

349

350 The stepwise multiple linear regression analysis (March-September mean  
351 temperature; none with a VIF >2) was significant (adjusted  $R^2 = 0.74$ ;  $p < 0.0001$ ),  
352 with sex (factor) and June temperatures as the most important variables ( $p < 0.0001$ )  
353 for predicting wing-length. These results do not change if we re-run the analysis while  
354 using collection locality as a factor variable (at the county scale) to predict wing-  
355 lengths across all specimens (i.e. not just those collected in years with three or more  
356 specimens; adjusted  $R^2 = 0.57$ ;  $p < 0.0001$ ; factor (county) not significant). Thus,  
357 locality at the county scale does not appear to influence wing-size in our dataset and  
358 was therefore excluded from subsequent analyses.

359

360 Due to the importance of sex for predicting wing length, we subsequently ran the  
361 stepwise multiple linear regression analyses for males and females separately. Males  
362 are significantly smaller than females (t-test,  $p < 0.0001$ ) and can be easily recognized  
363 by their scent scales, which form a distinct dark line on their dorsal forewings (Fig.  
364 1). Mean June temperature was the only significant variable for predicting male wing  
365 lengths (showing a positive relationship), for both August collected individuals  
366 (adjusted  $R^2 = 0.43$ ;  $p < 0.001$ ) and for those collected across all summer months (June –  
367 September; adjusted  $R^2 = 0.24$ ;  $p = 0.01$ ). Likewise, June was the only significant  
368 variable for analyses using minimum (adjusted  $R^2 = 0.33$ ;  $p = 0.002$ ) and maximum

369 (adjusted  $R^2=0.38$ ;  $p<0.001$ ) monthly temperature values. Mean June temperature  
370 alone can explain 39% of the variability in male wing lengths (Fig. 2c). There was no  
371 significant relationship between female wing lengths and mean monthly temperatures  
372 for August collected individuals ( $p=0.07$ ) or for females collected across all summer  
373 months ( $p=0.09$ ). Likewise, female wing lengths were not significantly related to  
374 minimum and maximum monthly temperatures. In addition, there was no significant  
375 relationship between male or female wing lengths and total monthly precipitation.  
376 Figure 2 shows that mean June temperature is a good predictor of male wing lengths,  
377 but female wing lengths cannot be well predicted by any of the variables.

378

379 The above results from the stepwise multiple linear regression analyses were reflected  
380 by the model selection analyses performed using the IT-AIC approach. Sex (factor)  
381 and mean June temperatures were the most important variables (importance scores of  
382 1.0) to predict wing lengths for the overall dataset (both males and females; Table 1).  
383 After nested models were removed, the only variables retained were sex (factor),  
384 June, and April (Table 1). Mean June temperature was the most important variable for  
385 predicting male wing lengths (importance score of 1.0; Fig. 2a; after nested models  
386 were removed, only June and May were retained; Table 2). Likewise, June was the  
387 most important variable (importance scores of 1.0) when models were run using  
388 minimum and maximum monthly temperatures. For females, April temperature  
389 (mean, minimum, maximum) was the most important variable for predicting wing  
390 length, but it was not present in all models (importance score 0.72 or lower; Fig. 2b;  
391 after nested models were removed, only April and June were retained; Table 2), nor is  
392 it significantly related to female wing length using ordinary linear regression  
393 ( $p>0.05$ ). For analyses relating precipitation to male and female wing length, July was

394 the most important variable - but it was not present in all candidate models  
395 (importance scores of 0.49 and 0.35 respectively) nor was it significantly related to  
396 male or female wing lengths using ordinary linear regression ( $p > 0.08$ ). Overall,  
397 monthly precipitation is a poor predictor of wing lengths. All results relating wing  
398 lengths to minimum/maximum monthly temperature and rainfall using the IT-AIC  
399 analyses can be found in SI tables 1-9.

400

401 To deal with potential scaling effects caused by the sexual size dimorphism, we  
402 calculated the slope of the natural log of wing lengths versus June temperatures,  
403 which was then transformed into a percentage change in wing length per °C using the  
404 formula:  $(\exp^{(\text{slope})} - 1) * 100$  (Forster, Hirst & Atkinson 2012; Horne, Hirst & Atkinson  
405 2015). There was a 2.20% increase in male wing length per °C compared with a  
406 0.90% increase in female wing length (though the regression itself is not significant,  
407 Fig. 2d), further showing that male wing sizes are more sensitive to change in June  
408 temperatures than female wing sizes.

409

410

411 PHENOLOGY

412

413 Between 1892 and 1973 sufficient specimens were available for analysis (i.e. five or  
414 more records in one year) in 40 of those years, providing a total of 437 useable  
415 records. The stepwise multiple linear regression analysis (no variables with a VIF  $> 2$ )  
416 shows that mean July temperature was the only significant variable to predict median  
417 collection dates (a negative relationship; adjusted  $R^2 = 0.42$ ;  $p < 0.0001$ ). For 10<sup>th</sup>  
418 percentile collection dates, mean July temperature and year were both significant  
419 (adjusted  $R^2 = 0.46$ ;  $p < 0.0001$ ), though year only was only weakly significant

420 ( $p=0.04$ ), indicating no long-term phenological trend in the response of *H. comma* to  
421 temperature. 10<sup>th</sup> percentile collection date advanced 3.8 days per 1°C increase mean  
422 July temperature (ordinary linear regression:  $R^2 = 0.36$ ;  $p < 0.0001$ ; Fig. 3c) and  
423 median collection date advanced by 5.1 days per 1°C increase in mean July  
424 temperature (ordinary linear regression:  $R^2 = 0.43$ ;  $p < 0.0001$ ; Fig3d). We found  
425 weak positive relationships between 10<sup>th</sup> percentile and median collection dates with  
426 April rainfall (ordinary linear regression:  $R^2 = 0.11$ ;  $p = 0.034$  and  $R^2 = 0.20$ ;  $p =$   
427  $0.004$  respectively). There were also significant negative relationships between 10<sup>th</sup>  
428 percentile and median collection date with minimum and maximum July temperatures  
429 as well as a slight positive relationship with July rainfall, but these variables were  
430 strongly correlated with mean July temperature.

431  
432 These results were also evident from the IT-AIC model selection analysis. Mean July  
433 temperature is the most important variable for predicting both 10<sup>th</sup> percentile and  
434 median collection dates (importance scores of 1.0; Fig. 3a,b; Table 3). When nested  
435 models were removed, July, year, April and September were retained for analyses  
436 predicting 10<sup>th</sup> percentile collection date; whereas only July was retained to predict  
437 median collection dates (Table 3). Likewise, July was the best predictor of collection  
438 dates when models were run with minimum and maximum monthly temperatures  
439 (importance scores of 1.0). For rainfall, July was the most important month for  
440 predicting 10<sup>th</sup> percentile collection dates (importance score = 0.98) and April was the  
441 most important variable for predicting median collection dates (importance score =  
442 0.98), closely followed by July rainfall (importance score = 0.86); but as described  
443 above, April and July rainfall are only weakly related to collection date. All results  
444 relating collection dates to minimum/maximum monthly temperature and rainfall  
445 using the IT-AIC analyses can be found in SI tables 10-15.

446

447 **Discussion**

448

449 Determining how different life stages of a species separately and collectively respond  
450 to temperature is essential for understanding the ecological and evolutionary  
451 consequences of climate change (Kingsolver *et al.* 2011; Buckley *et al.* 2015). Here,  
452 we show that changes in wing length and phenology of the univoltine butterfly,  
453 *Hesperia comma*, are partly dependent upon temporal variation in monthly summer-  
454 time temperatures during key stages of their life cycle (Fig. 4). June temperatures,  
455 when larvae are in the final larval instar, are important for predicting adult wing  
456 length (but only for males). July temperatures, during the pupal stage, are important  
457 for predicting timing of adult emergence (phenology). Finally, August temperatures,  
458 during the adult stage, have recently been shown to be important for predicting  
459 geographic range expansion during years with warm August temperatures and  
460 localized extinction during years with cooler August temperatures (Lawson *et al.*  
461 2012; Lawson *et al.* 2013). Our study would not be possible without long time-series  
462 data from digitized natural history collections paired with monthly temperature  
463 records (for wing length and phenology), previously published data from field surveys  
464 over recent decades (for range change), and extensive prior knowledge of the life  
465 cycle and natural history of *H. comma* (Thomas *et al.* 1986; Thomas *et al.* 2001;  
466 Davies *et al.* 2006; Lawson *et al.* 2012; Lawson *et al.* 2013).

467

468 Advancement in adult emergence dates and range expansion has commonly been  
469 reported for northern temperate butterfly species in recent years (Parmesan *et al.*  
470 1999; Breed, Stichter & Crone 2013; Brooks *et al.* 2014; Kharouba *et al.* 2014), but

471 these responses have not been examined alongside body size change. Until recently, it  
472 was thought that warming will cause widespread declines in body size of ectotherms  
473 because they burn more metabolic energy when it is warmer and thus, need more food  
474 to achieve and maintain large body sizes at higher temperatures (Bickford, Sheridan  
475 & Howard 2011; Ohlberger 2013). If increased consumption is not sustainable, then a  
476 shift towards smaller individuals over time is predicted with warming (Sheridan &  
477 Bickford 2011). While this may be true for a number of ectotherms (particularly for  
478 aquatic species; Forster, Hirst & Atkinson 2012), we now know that voltinism is also  
479 an important factor influencing the direction of the temperature-size response, at least  
480 among terrestrial arthropods (Horne, Hirst & Atkinson 2015). Univoltine species (e.g.  
481 some butterflies) appear to get larger with increasing temperatures, whereas  
482 multivoltine species show the opposite response. Our study mirrors this result, which  
483 we believe to represent the first support of the ‘converse Bergmann cline’  
484 (Blanckenhorn & Demont 2004) using a temporal rather than a spatial or laboratory  
485 dataset in insects (see Teplitsky & Millien (2014) for an endothermic study).

486

487 Interestingly, our results suggest that male wing sizes are more responsive than  
488 females to temperature, also noticed in field studies of other butterfly species  
489 (Gilchrist 1990). Males are significantly smaller than females as adults (Fig. 1), which  
490 is common across insects and largely due to longer female development times (Teder  
491 2014). Assuming that the relative size difference between male and female adults is  
492 also found in their respective final larval instar, then variation in June temperatures  
493 will affect growth of male caterpillars more than females simply due to differences in  
494 surface area to volume ratio (smaller individuals lose heat faster than large  
495 individuals). Thus, cold June temperatures should disproportionately restrict the

496 growth of smaller caterpillars (males) compared to larger caterpillars (females),  
497 though possible differences in microhabitat may also be an important, yet largely un-  
498 tested variable (Kingsolver *et al.* 2011). In addition, field surveys indicate that males  
499 tend to emerge earlier than females (Hill, Thomas & Lewis 1999), though this was not  
500 evident in our dataset. Earlier emergence (and shorter developmental time) could  
501 mean that males experience different temperatures (and/or more extreme  
502 temperatures) than females for some portion of their life cycle, which may also  
503 contribute to our findings. Furthermore, warmer June temperatures may improve  
504 larval food quality (*Festuca ovina*) and increase rate of feeding (Higgins *et al.* 2014),  
505 leading to larger adult sizes. Finally, and in line with predictions from Horne, Hirst &  
506 Atkinson (2015), years with warm June temperatures are, on average, likely to have  
507 more days of sunshine, effectively producing a longer larval growing season leading  
508 to increased size of the final instar and subsequent adult size. But why this would  
509 affect males and not females remains unclear. One possibility is that the upper range  
510 of female body sizes is more constrained compared to males given that they are the  
511 larger sex and maximum body size should be set within physiological limits;  
512 suggesting that females are already near their upper size limits whereas males have  
513 more scope for change. Interestingly, years with the warmest average June  
514 temperatures in our dataset (16.4°C) have males with relatively small wing sizes,  
515 indicating that the upper limit to male wing size may occur just below this  
516 temperature threshold (Fig. 2c). Although it requires further study, our results provide  
517 further support that climate variability may contribute to the magnitude of sexual size  
518 dimorphism (Stillwell *et al.* 2010).  
519

520 Incorporating the interactive effects of each response (body size, phenology, range  
521 change) will be a key, yet challenging, step towards a comprehensive understanding  
522 of the ecological effects of climate change (Kingsolver *et al.* 2011; McCauley &  
523 Mabry 2011). In *H. comma* for example, Hill, Thomas & Lewis (1999), found that the  
524 most rapidly expanded portions of its range in Britain were composed of individuals  
525 that had a higher relative investment in thorax size, which is primarily composed of  
526 muscles used in flight. While we did not measure thorax size (due to the probability  
527 of shrinkage for old specimens) and the temporal scope of our study (1880-1973) is  
528 prior to the more recent range expansion, we do show that male wing sizes get larger  
529 during years with warm June temperatures. Across butterfly species, larger wings  
530 (and other life history traits) are often associated with longer dispersal distances  
531 (Hughes, Dytham & Hill 2007; Stevens *et al.* 2013). Thus, if wing sizes scale  
532 positively with seasonal temperature across univoltine species, then range expansions  
533 (assuming habitat is available) would be more likely during years with warm  
534 temperatures during both the final larval instar and adult stages. This scenario implies  
535 an interactive effect of body size on distribution, but an interaction of distribution on  
536 body size should also be apparent. *Hesperia comma* adults are smallest at the very  
537 northern edge of the range in Scandinavia, where summer temperatures are cool  
538 (Dennis & Shreeve 1989; though they did not distinguish between males and  
539 females), which we would predict based on the positive relationship between  
540 temperature and male wing size (Fig. 2). There are likely to be other interactive  
541 effects (distribution and phenology, e.g. Diamond *et al.* 2011; body size and  
542 phenology; e.g. Kharouba *et al.* 2014) but the current lack of long-term *H. comma*  
543 studies outside of southern England precludes much discussion (but see Karlsson  
544 2014). Further, the influence of microhabitat (e.g. slope and aspect of chalk hills,

545 sward height) on the temperature experienced by the larval, pupal, and adult stages,  
546 which is often a key component of field based ecological studies of *H. comma*  
547 (Thomas *et al.* 2001; Davies *et al.* 2006), may have caused some of the unexplained  
548 variation in our results.

549

550 We have used historical data and previous research to link monthly summer  
551 temperature variation during key stages of the life history of *H. comma* to respective  
552 changes in body size, phenology, and range change. Historically however, years with  
553 warm June temperatures did not necessarily also have both warm July and August  
554 temperatures. Yet in the near future, one may expect it will be more common to have  
555 years when these months are collectively warmer than they were in the past. Based on  
556 our results, this would result in relatively large males, earlier emergence, and  
557 continued range expansion (Fig. 4). However, the possibility of further range  
558 expansion will be highly dependent upon habitat availability and appropriate habitat  
559 management for this species.

560

561 Where available, natural history collections paired with associated meta-data can be  
562 used to establish a baseline of ecological response to temperature variation before the  
563 onset of modern climate warming. Such studies are needed in conjunction with  
564 continued long-term monitoring of relevant traits (e.g. body size, phenology,  
565 abundance, distribution) and sustained specimen collection deposited in natural  
566 history museums (Johnson *et al.* 2011) as a part of the greater goal of understanding  
567 the ecological and evolutionary consequences climate change. Moreover, studies  
568 assessing the consequences of climate change for organisms with complex life cycles,  
569 where different environments are experienced during different life stages, must take

570 into account the differing responses of each life stage (Kingsolver *et al.* 2011). We  
571 show that changes may be predictable at the intraspecific scale if long-term data are  
572 integrated with knowledge of the life history and ecology of a species. But scaling up  
573 predictions established for single species to the community level and across varying  
574 spatial scales will be a greater challenge (but see Hinks *et al.* 2015). General patterns  
575 may emerge once each “universal” ecological response to climate change and their  
576 interactions are explored intraspecifically, followed by comparative analyses across  
577 taxonomic groups with different modes of life and habitat requirements.

578

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587

### 588 **Data accessibility**

589 Data available from the Dryad Digital Repository:

590 <http://dx.doi.org/10.5061/dryad.r2250>

591

592

593 **Fig. 1**

594 Boxplots of all August collected male (n=217) and female (n=202) forewing lengths  
595 of *H. comma* specimens. Males have significantly smaller forewing lengths than  
596 females and can be distinguished by a dark band of scent scales on each forewing.  
597 The white dotted lines illustrate specimen forewing lengths.

598

599 **Fig. 2**

600 Coefficient (slope) estimates for each variable (March – September mean monthly  
601 temperature and year) to predict a) male wing lengths and b) female wing lengths  
602 using the IT-AIC approach. June is the only variable that was found in all candidate  
603 models (importance score of 1.0) for predicting male wing lengths, with slope  
604 estimates not including zero. For females, none of the variables were found in all  
605 candidate models and all had slope estimates that include zero. The bottom panels  
606 show the significant linear regression of c) male wing lengths and d) the non-  
607 significant regression of female wing lengths versus June temperature. Each point  
608 represents the median value of forewing lengths for years with at least three  
609 specimens (n=28 years from 1892-1973 for males; n=30 years from 1880-1971 for  
610 females).

611

612 **Fig. 3**

613 Coefficient (slope) estimates for each variable (March – September mean monthly  
614 temperature and year) to predict a) 10<sup>th</sup> percentile collection day and b) median  
615 collection day using the IT-AIC approach. July was the only variable present in all  
616 candidate models (importance scores of 1.0) for predicting both 10<sup>th</sup> percentile and  
617 median collection days, with slope estimates not including zero. All of the slope

618 estimates for non-July variables include zero. The bottom panels show the significant  
619 linear regressions of c) 10<sup>th</sup> percentile and d) median collection days versus July  
620 temperature. Each point represents values for years with at least five specimens (n=40  
621 years, spanning from 1892-1973).

622

623 **Fig. 4**

624 Climate change affects the body size, phenology and geographic range of a species. In  
625 the Silver-spotted Skipper (*Hesperia comma*) in Britain, male body size is correlated  
626 with June temperatures during the final larval instar, adult emergence is correlated  
627 with July temperature during the pupal stage, and geographic range change is linked  
628 with August temperature during the adult stage.

629 **Table 1.** Parameter estimates for the candidate models using information criteria ( $\Delta AIC < 7$ ) for predicting wing lengths of all individuals  
 630 (males and females). In addition to sex, predictor variables include year and mean monthly temperatures (March-September) when *H. comma*  
 631 individuals are in the larval through adult stages of their life cycle in southern England. An importance score of 1.0 means that a variable was  
 632 present in all candidate models. Columns are ordered in descending order by importance score. Coefficient estimates (slope) are averaged over  
 633 all the candidate models. Variables in bold are those that were retained when nested models were removed.

634

	<b>Factor (sex)</b>	<b>JUN</b>	<b>APR</b>	SEP	MAY	MAR	AUG	Year	JUL
Importance scores	1.0	1.0	0.68	0.42	0.42	0.37	0.31	0.25	0.24
N containing models	102	102	60	50	48	47	43	42	43
Coefficient estimate	-1.32	0.22	0.11	0.10	-0.09	-0.05	-0.06	0.00	0.04
Std. Error	0.12	0.06	0.06	0.07	0.07	0.05	0.06	0.00	0.06
Adjusted Std. Error	0.12	0.06	0.06	0.08	0.07	0.05	0.07	0.00	0.07
Lower CI	-1.55	0.10	-0.01	-0.05	-0.22	-0.15	-0.19	-0.01	-0.09
Upper CI	-1.08	0.35	0.22	0.25	0.05	0.04	0.07	0.00	0.17

635

636

637  
 638 **Table 2.** Importance scores and number of candidate models containing each variable (mean monthly temperatures and year) when analyses are  
 639 separately run to predict male and female wing lengths using information criteria ( $\Delta AIC < 7$ ). Columns are ordered in descending order by  
 640 importance score. The predictor variables include year and mean monthly temperatures (March-September) when *H. comma* individuals are in  
 641 the larval through adult stages of their life cycle in southern England. Coefficient estimates with confidence intervals are shown graphically in  
 642 Figs 2a and b. Variables in bold are those that were retained when nested models were removed.

643  
 644

<b>Males</b>	<b>JUN</b>	<b>MAY</b>	SEP	APR	AUG	MAR	JUL	Year
Importance scores	1.0	0.65	0.18	0.18	0.18	0.16	0.15	0.15
N containing models	43	22	12	12	12	12	11	11
<b>Females</b>	<b>APR</b>	<b>JUN</b>	SEP	MAR	AUG	JUL	Year	MAY
Importance scores	0.67	0.51	0.31	0.28	0.22	0.21	0.19	0.15
N containing models	69	57	49	45	42	39	36	31

645

646 **Table 3.** Importance scores and number of candidate models containing each variable (mean monthly temperatures and year) when analyses are  
 647 separately run to predict 10<sup>th</sup> percentile collection day and median collection day using information criteria ( $\Delta AIC < 7$ ). Columns are ordered in  
 648 descending order by importance score. An importance score of 1.0 means that a variable was present in all candidate models. The predictor  
 649 variables include year and mean monthly temperatures (March-September) when *H. comma* individuals are in the larval through adult stages of  
 650 their life cycle in southern England. Coefficient estimates with confidence intervals are shown graphically in Figs 3a and b. Variables in bold are  
 651 those that were retained when nested models were removed.

652

<b>10<sup>th</sup> percentile collection day</b>	<b>JUL</b>	<b>Year</b>	<b>APR</b>	<b>SEP</b>	MAY	JUN	MAR	AUG
Importance scores	1.0	0.88	0.61	0.35	0.27	0.19	0.17	0.16
N containing models	53	40	27	28	19	16	15	15
<b>Median collection day</b>	<b>JUL</b>	Year	APR	JUN	MAY	SEP	MAR	AUG
Importance scores	1.0	0.44	0.32	0.27	0.24	0.18	0.18	0.18
N containing models	69	31	29	27	26	22	21	22

653  
654

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