

Microclimate and resource quality determine resource use in a range-expanding herbivore.

Journal:	Biology Letters
Manuscript ID	RSBL-2021-0175.R1
Article Type:	Research
Date Submitted by the Author:	16-Jun-2021
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Subject:	Behaviour < BIOLOGY, Ecology < BIOLOGY
Categories:	Global Change Biology
Keywords:	ectotherm, host shift, Lepidoptera, local adaptation, thermal biology, <i>Aricia agestis</i>

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Ethics

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This manuscript is based on original research on wild insects which adheres to the Royal Society's ethics standards, ASAB's Guidelines for the Use of Animals in Research, legal requirements in the United Kingdom and institutional guidelines at the University of Exeter. This manuscript is not published or under consideration for publication elsewhere. Permission to conduct fieldwork at Holkham NNR was granted by Holkham Estate and Natural England.

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The supporting data are available via the Dryad repository at

https://doi.org/10.5061/dryad.3ffbg79j1. The supportiNg R code is available via Zenodo at https://doi.org/10.5281/zenodo.4898844

Stewart JE, Maclean IMD, Edney AJ, Bridle J, Wilson RJ. 2021 Data from: Microclimate and resource quality determine resource use in a range-expanding herbivore. Dryad Digital Repository. (doi: 10.5061/dryad.3ffbg79j1)

Stewart JE, Maclean IMD, Edney AJ, Bridle J, Wilson RJ. 2021 R Code from: Microclimate and resource quality determine resource use in a range-expanding herbivore. Zenodo. (doi:10.5281/zenodo.4898844)

Conflict of interest

I/We declare we have no competing interests

Statement (if applicable):

CUST_STATE_CONFLICT : No data available.

Authors' contributions

This paper has multiple authors and our individual contributions were as below

Statement (if applicable):

JES conceived of and designed the study with input from IMDM, JB and RJW. JES and AJE carried out the fieldwork, and JES carried out the statistical analysis and drafted the manuscript. All authors helped to draft and/or critically revise the manuscript, gave final approval for publication and agree to be held accountable for the work performed therein.



- 1 Title: Microclimate and resource quality determine resource use in a range-expanding
- 2 herbivore.
- 3 Running Head: Insect egg-laying and microclimate
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Abstract

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19 The consequences of climate change for biogeographic range dynamics depend on the spatial scales at which climate influences focal species directly, and indirectly via biotic 20 interactions. An overlooked question concerns the extent to which microclimates modify 21 22 specialist biotic interactions, with emergent properties for communities and range dynamics. 23 Here, we use an in-field experiment to assess egg-laying behaviour of a range-expanding herbivore across a range of natural microclimatic conditions. We show that variation in 24 25 microclimate, resource condition, and individual fecundity can generate differences in egg-26 laying rates of almost two orders of magnitude in an exemplar species, the brown argus butterfly (Aricia agestis). This within-site variation in fecundity dwarfs variation resulting from 27 28 differences in average ambient temperatures among populations. Although higher 29 temperatures did not reduce female selection for host plants in good condition, the thermal 30 sensitivities of egg-laying behaviours have the potential to accelerate climate-driven range 31 expansion by increasing egg-laying encounters with novel hosts in increasingly suitable 32 microclimates. Understanding the sensitivity of specialist biotic interactions to microclimatic 33 variation is therefore critical to predict the outcomes of climate change across species' geographic ranges, and the resilience of ecological communities. 34 35 Keywords: Aricia agestis, ectotherm, host shift, Lepidoptera, local adaptation, thermal 36 biology

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Background

Responses to climate change occur through a combination of geographic range shifts [1,2] and in situ plastic and genetic changes that modify the phenology, behaviour or resource use of phenotypes [1,3,4]. These changes determine the abundance, distribution and persistence of species and their biotic interactions [1,5–8]. Where biotic interactions are specialised (e.g. feeding by many phytophagous insects), they create locally suitable habitat patches with steep 'suitability gradients' at patch edges [9], embedded within a matrix of unsuitable habitats which limit dispersal and colonization. Specialist interspecific interactions can therefore constrain range expansion [10,11]. The effects of climate change on how individuals encounter, select and exploit resources, or on resource quality itself, could alter range dynamics by smoothing or steepening existing suitability gradients, for example by promoting or precluding certain biotic interactions [12– 17]. Research on Lepidoptera host use suggests that range expansion itself promotes incorporation of novel hosts in herbivore diets [18,19], while egg shortfall related to the availability of suitable (micro)habitats and climatic conditions is an important limiting factor at species' range margins [20,21]. Therefore, understanding how individuals' behaviours are mediated by local conditions during species' interactions such as host selection represents a critical step in predicting ecological and evolutionary outcomes of climate change, but is often overlooked [22–25]. Assessments of responses to environmental change also rarely account for the sub-daily and sub-metre temporal and spatial resolutions over which interaction partners and climate vary [26,27]. Such fine-scale variation influences individual behaviour, resource acquisition and fitness, understanding of which may be critical to predict broader ecological responses to climate change [28–35]. In this paper, we consider how the steepness of habitat suitability gradients may be modified by individual responses to variation in microclimate and resource condition. We use as a case study a specialist butterfly that has undergone a rapid range expansion associated with the evolution of its biotic interactions to exploit more widespread novel host plants [5,11]. Until the 1990s, the UK distribution of the brown argus butterfly (*Aricia agestis*, Lycaenidae) was largely restricted to calcareous grasslands, where it used the perennial common rockrose (Helianthemum nummularium, Cistaceae) as its main larval host [36]. Since then, populations have colonised formerly unsuitable regions by increasingly (and apparently exclusively) exploiting Geraniaceae, including the annuals *Erodium cicutarium*, *Geranium* dissectum and G. molle [5,11,14,37,38]. Studies suggest that warming has enabled increasing use of Geraniaceae and persistence of populations in areas that were previously too cool, coupled with evolutionary changes to increase the frequency of females using only Geraniaceae as hosts [5,11,14,37,39]. These analyses have focused on changes in coarse climate metrics (i.e. Central England Temperature). However, temperature variation at finer scales can dwarf that observed more broadly [26,40]. For example, ground-level

- temperatures of south-facing grasslands in England can be >15 °C warmer than adjacent
- north-facing slopes [41]. Understanding how microclimate determines egg-laying behaviour
- in this species can therefore act as a model for the effects of warming on a biotic interaction
- that determines ecological and evolutionary range dynamics.
- 79 We test the extent to which within-site microclimatic temperature variation affects egg-laying
- 80 behaviour of individual butterflies on the novel host *G. dissectum*. We show that individual
- responses to variation in microclimate and the condition of host plants can generate 75-fold
- 82 differences in egg-laying rates. These exogenous drivers of expressed fecundity could
- therefore have important impacts on broader-scale host use and range dynamics, by
- smoothing or steepening habitat suitability gradients at range margins.

Methods

- 86 Experimental approach
- We carried out experiments on wild-caught female brown argus between 5th August and 7th
- 88 September 2017 to test how natural microclimatic variation mediates *in situ* egg-laying
- behaviours on *G. dissectum*, a Geraniaceae species widely used as a larval host in recently
- 90 established populations [14]. We established 25 experimental cages (Figure 1a) in the dune
- 91 system of Holkham National Nature Reserve (Norfolk, UK), in locations chosen to represent
- 92 the local range of slopes and aspects (Appendix 1). At 30 minute intervals, we measured in-
- cage ground-level temperatures (two dataloggers per cage), ambient temperatures (single
- datalogger with Stevenson screen 1.5 m above ground) and ground-level air temperatures
- 95 (29 individual dataloggers at randomly-selected locations across the site) (Appendix 1).
- 96 Cages contained ≥95% bare ground, no natural host plants, and two greenhouse-grown
- 97 G. dissectum ('experimental hosts') per cage (Figure 1a; Appendix 1). Ground albedo and
- degree of thermal coupling between ground and air temperature will therefore have been
- 99 similar between cages, and representative of microclimates in open dune areas [42], where
- 100 A. agestis lay eggs on wild Geraniaceae at this site. Differences between cages in slope,
- aspect and topographic shading likely caused large variation in net radiation absorbed by the
- ground, thereby generating large variation in cage temperatures (microclimates) for a given
- ambient temperature. In-cage microclimates were representative of the range and averages
- of ambient and ground-level temperatures experienced at the site (Figure 1b; Appendix 1).
- All experimental hosts were watered daily and, though our experimental focus was on
- microclimatic temperature variation, we monitored host condition and phenophase every two
- days, to quantify temporal variation in plant traits that may influence acceptability for egg-
- laying. Host plant condition was visually assessed on a scale of 0–3 (poor–high quality for
- egg-laying, following [36]; see Appendix 1 for details and justification), and phenophase was
- recorded on a four-point scale describing whether the plant was in leaf, bud, flower or had

set seed. Average plant condition within cages was maintained at ≥2.0 by replacing plants

112	that deteriorated to category 2, and plants were typically replaced before flowers were visible
113	(<5% of cage exposures included one flowering plant). This was achieved by growing 240
114	plants in four cohorts over a six-week period, so all plants used were similar in age, condition
115	and phenophase. Adult female butterflies were captured and housed individually in mesh
116	pots overnight prior to individual release into experimental cages (see Appendix 1 for
117	husbandry).
118	Females were individually assigned to cage exposures each morning, in a pseudo-
119	randomised manner to control for order effects (Appendix 1). A total of 109 females were
120	exposed to host plant and thermal environments during 433 cage exposures. To avoid
121	including data from unmated females, we use data from those 43 females which laid during
122	at least one exposure. These females experienced 251 exposures (5.8 \pm 2.8 (SD) exposures
123	each) lasting on average 7 h 49 m (± 47 m (SD)) per exposure. After each exposure, all
124	experimental hosts were systematically searched for eggs; because there were only two
125	plants per cage it was possible to find all eggs, which were removed to avoid double
126	counting. Plant phenophase and the condition of the focal leaf and plant were recorded for
127	each egg-laying location. Post-exposure, butterflies were housed overnight in mesh pots
128	before release into a new cage on the following days. We consider data from all exposures
129	occurring between the hours of 07:30–18:30 which included at least six hours of favourable
420	weather (Appendix 1).
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131	weather (Appendix 1). Analysis
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131 132 133 134 135 136 137 138 139 140 141 142 143	We modelled egg-laying probability per exposure using logistic regression with 'Ime4' [43]. For exposures in which eggs were laid, hourly egg-laying rate was modelled using a gamma GLMM (log link) with 'glmmTMB' [44]. For both analyses we considered female ID as a random intercept term (to account for individual variability due to factors such as age) and mean cage temperature (during the appropriate exposure for each cage) as a candidate random slope term representing among-individual variation in thermal sensitivity. As candidate fixed effects, we considered cage temperature (mean temperature of the relevant cage during the exposure) and its quadratic term, exposure number (whether it was the individual's 1st, 2nd, etc. exposure), study day and cumulative eggs laid in prior exposures as scaled continuous predictors, and mean host plant condition and phenophase as ordered factors (with three and five factor levels respectively; Appendix 1). We also tested for a host condition-cage temperature interaction. We constructed candidate model sets by considering all plausible parameter combinations,

- 148 was tested with simulation-based power analyses (Appendix 1). We used R version 3.5.1 149 [45-47]. Results 150 Egg-laying probability increased as a function of in-cage temperature (Table 1; Figure 1c), 151 such that the odds of laying increased by 27% per 1 °C temperature increase. There was 152 also a negative effect of study day (Table 1; Figure S4); candidate models showed limited 153 support for positive effects of exposure number and host condition. There was no support for 154 effects of prior laying experience or host phenology in models of egg-laying probability or 155 156 rate (Table 1). Egg-laying rate increased as a function of in-cage temperature and host condition (Figure 157 1d): by ~12% per 1 °C (Figure 1e), and by a factor of ~7.9 on good vs poor condition hosts 158 (Figure 1f). This equates to an egg-laying rate that is ~75 times higher on the best condition 159 hosts in the warmest microclimate than on the poorest condition hosts in the coolest 160 microclimate. Candidate models showed limited support for a positive effect of exposure 161 number and a negative effect of study day (Table 1). 162 The random effect variance (Table 1) demonstrates between-individual variation in egg-163 laying probability (LRT = 9.016, p = 0.003) and rate (LRT = 10.903, p < 0.001). There was no 164 support for inclusion of random slopes regarding temperature for laying probability (LRT = 165 0.065, p = 0.968) or rate (LRT = 0.974, p = 0.615): females differed in their fecundity overall 166 167 but not in their sensitivity to temperature. Power analyses demonstrated low power to detect random slopes (5.6% in a model of laying probability; Appendix 1). 168 169 **Discussion** 170 We assessed egg-laying on a novel host across a temperature range that is representative 171 of natural microclimates, but wider than the mean ambient temperature range typically experienced by the range-expanding brown argus butterfly across England [11]. Our data 172 show that individual responses to variation in microclimates and host plant condition can 173 174 combine to generate differences in egg-laying rates that are almost two orders of magnitude greater than population-average differences in egg-laying rates observed between host 175 species [14]. 176 Egg-laying females were remarkably sensitive to small variations in host condition, a factor 177 we sought to minimise in our experiment. This is the first time such discrimination has been 178 179 shown in the Geraniaceae hosts used in the brown argus' range expansion, and 180 complements a previous [36] demonstration that females select lush green leaves (with thick
 - H. nummularium. Compared to H. nummularium, the condition of wild Geraniaceae hosts
 - appears more temporally variable [48]. As annuals, Geraniaceae may be less reliable

mesophylls and high nitrogen content) when laying on the traditional perennial host,

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184	resources in terms of quality and availability at a fine spatial scale, even though they are
185	more widely distributed at larger scales [37,49]. In this context, the bottom-up influences of
186	plant phenotypic variation can provide a strong mechanistic basis for understanding
187	population dynamic responses to global change in herbivores and plants [3,50,51].
188	A methodological concern is that cage experiments may eliminate use of long-distance, pre-
189	alighting cues for egg-laying site choice such as habitat structure or odour plumes of plant
190	volatile compounds (e.g. [52]). Such cues could have altered the acceptability of the host
191	plants with which the butterflies were confined (for example, relative to other host species).
192	However, observations of eggs laid on natural hosts by free-flying brown argus suggest
193	similar preferences regarding host condition [48]. These observations suggest either that the
194	cage experiments do not introduce cue bias, or that long-distance and short-distance cues
195	are well-correlated, as observed in some other species [53]. Furthermore, G. dissectum is
196	often preferred in direct choices between host species, though population-level host species
197	preference varies between sites [14].
198	The odds and rate of egg-laying increased dramatically with microclimatic temperature (by
199	27% and 12% per 1 °C, respectively). Warming may therefore increase population growth
200	through increased fecundity, provided suitable hosts are available. At ecological margins,
201	warming also increases the distribution and connectivity of microhabitats that are suitable for
202	egg laying [21]. Microclimatic variation could thereby drive range expansion at a faster rate
203	than ambient temperatures would predict, and may account for recent range expansions by
204	temperature-sensitive species across previously unsuitable landscapes [11,54,55].
205	Behavioural thermoregulation in ectotherms (e.g. basking), allows some thermal
206	independence from the environment. However, many species (including the brown argus)
207	are more dependent on microhabitat selection and their immediate thermal environment for
208	thermoregulation [30]. Fine-scale temperature variation in the immediate proximity of
209	resources may therefore have important effects on population responses to climate change
210	[28–30,56,57].
211	In our experiment, the relationship between egg-laying rate and host condition did not vary
212	with temperature. Though this experiment did not address inter-species host preferences,
213	these results suggest that warming alone may not explain the concurrent host and range
214	shifts observed in this species. Given the odds and rate of egg-laying increase dramatically
215	with microclimatic temperature, warmer summers may increase the likelihood of females
216	encountering and sampling alternative hosts in newly favourable microclimates, increasing
217	the probability of host shifts during range expansion [18]. Larvae grow 10% larger and faster
218	on Geraniaceae than on <i>H. nummularium</i> [5,58], provided temperatures are high and
219	relatively stable. This may combine with increased fecundity to promote establishment and
220	growth of populations using the novel host plants, once threshold temperatures are reached.

221	Beyond the potentially beneficial effects of warming on herbivore population growth, further
222	warming may generate maladaptive behaviours. For example, if host condition is correlated
223	with local temperature or moisture regimes then high egg-laying rates under warm, dry
224	conditions may increase herbivore mortality through exposure to poor condition, desiccated
225	hosts. Inflexible preferences for plants growing in drought-stressed habitats were
226	maladaptive for Melitaea cinxia butterflies in an extremely dry year, reducing population
227	persistence [59]. Given the capacity for behavioural responses to the environment to
228	become maladaptive as climates change, there is a need for better understanding of genetic
229	variation among individuals and the potential for the evolution of novel behaviours [35]. With
230	this in mind, although we found significant among-individual variation in fecundity (random
231	intercepts), our experiment had insufficient power to detect significant among-individual
232	variation in behaviour [60,61].
233	Here, we show how biotic interactions can be determined by individual responses to
234	variation in microclimate and resource condition. Spatial variation in microclimate may
235	therefore be crucial in determining the steepness of habitat suitability gradients, which
236	regulate rates of range expansion in fragmented landscapes [62]. Advances in modelling
237	fine-scale spatial and temporal variation in microclimate can increasingly reveal when
238	climatic conditions acting on individuals or biotic interactions regulate such range expansions
239	[40,63,64]. Such approaches may permit a mechanistic understanding of range shifts, and
240	higher resolution models of species distributions [48,65,66]. Incorporating robust evidence of
241	the effects of microclimate and biotic interactions on range dynamics may thus improve
242	understanding and prediction of ecological responses to climate change.

Acknowledgments

- 244 C. Milne, S. Speak, S. Henderson and Holkham estate staff assisted with fieldwork.
- 245 Research was funded by the Natural Environment Research Council (grant NE/L002434/1 to
- JES). Holkham Estate and Natural England kindly granted research permits. Thanks to Rosa
- Menéndez and Jon Bennie for helpful comments on the research, and to Susanne Foitzik,
- 248 Ed Turner, and three anonymous reviewers for their contributions through the review
- 249 process.

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Table 1. Summary of AIC analyses for GLMMs of egg-laying probability (LP) and rate (LR). Showing models with Δ AIC \leq 6, including the best AIC model (M_{AIC}), selected model (M_{final}) and null model (M_{null}). Parameter estimates (with standard errors) are shown for the intercept (β_0), study day (D), exposure number (E), mean cage temperature (T) and mean host condition (Q). Q is an ordered factor with orthogonal polynomial contrasts: estimates are presented for the linear (Q_L) and quadratic terms (Q_Q). Variance of the female ID random intercept term is denoted V_{RE} . LL is the log-likelihood.

Model	Model parameters							ΔΑΙС	
Model	$oldsymbol{eta}_{o}$	D	Ε	Τ	Q_L	Q_Q	V_{RE}	LL	ДАІС
LP _{AIC}	0.194 (0.351)	-0.877 (0.253)	0.334 (0.212)	1.090 (0.197)	0.866 (0.647)	0.035 (0.462)	0.716	-133.71	0.00
LP_a	0.616 (0.215)	-0.855 (0.247)	0.306 (0.209)	1.023 (0.190)	_	_	0.712	-135.74	0.06
$\mathit{LP}_{\mathit{final}}$	0.587 (0.213)	-0.648 (0.203)	_	1.006 (0.188)	_	_	0.736	-136.83	0.25
LP _{null}	0.542 (0.195)	_	0,	_	_	_	0.664	-162.12	46.83
LR _{AIC}	-0.231 (0.189)	-0.241 (0.118)	0.205 (0.103)	0.428 (0.084)	1.593 (0.351)	-0.331 (0.243)	0.223	-248.84	0.00
$LR_{\it final}$	-0.207 (0.196)	-	_	0.441 (0.085)	1.458 (0.345)	-0.276 (0.241)	0.279	-251.12	0.57
LR _{null}	0.649 (0.126)	-	-		_	-	0.266	-269.38	31.08

Figure legends

Figure 1. (a) Experimental cage with two greenhouse-grown *Geranium dissectum* and iButton dataloggers. (b) Daily minimum, mean and maximum temperature across all cages (In-cage), compared with daily average across 29 iButtons distributed randomly at ground level around the site outside of cages (Ground), and ambient temperature measured at 1.5 m above ground (Ambient) (c) Probability of egg-laying increases with mean cage temperature (model LP_{final}). Point clouds indicate exposures during which eggs were (1) and were not (0) laid, lines represent among-female variation. (d) Mean egg-laying rate grouped by host condition and mean cage temperature (range = 13.7 - 34.3 °C; grouping for display only) during the relevant exposure; bar labels show sample size. (e) Marginal effects of mean cage temperature on egg-laying rate; lines show among-female variation (model LR_{final}), points show raw data. (f) Egg-laying rate grouped by host condition, showing marginal effects (model LR_{final}), 95% confidence intervals, and raw data (coloured points).

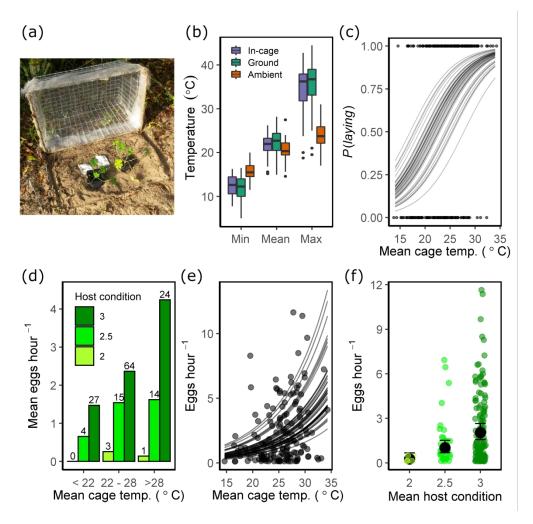


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