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1 **National-scale declines in Lepidoptera populations consistent with modelled impacts of**
2 **climate change.**

3 Running head: Climate change and Lepidoptera

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19 Weather

20

21 **Abstract**

22 Lepidoptera are sensitive to climate change, with documented impacts on their phenology,
23 distribution and communities. However, there remains considerable uncertainty over which
24 species are most vulnerable, and which have been most affected so far. To address this, we
25 analyse 35-year UK or English population trends of 55 butterfly and 265 moth species to
26 model the impacts of variation in temperature and precipitation upon population growth rates.
27 We identify the weather variables and periods that species are most sensitive to, the long-
28 term impacts of climate change, and the characteristics of species which show the greatest
29 responses. Positive impacts of summer temperature on both butterflies and moths were partly
30 offset by negative impacts of temperature in other seasons, particularly winter. Precipitation
31 tended to have negative impacts on population growth rates, particularly for moths. Annual
32 population fluctuations were strongly driven by inter-annual variation in weather conditions.
33 Over 40% of a significant decline in mean moth abundance from the 1990s to 2000s was
34 consistent with a weather-driven decline predicted by our models, which also explained up to
35 19% of the decadal variation in abundance between species. Species overwintering as larvae
36 and multivoltine species were most sensitive to the effects of weather, whilst southerly-
37 distributed species, species associated with woodland and unimproved grassland habitats, and
38 pest species, showed the most positive long-term responses to climate change. Combined,
39 these results show how climate change is already having significant impacts on the
40 abundance of particular butterfly and moth species, with likely future consequences for
41 ecosystem function and services.

42

43 **1. Introduction**

44 Climate change is an increasing threat to natural systems, the biodiversity they support and
45 the ecosystem services they provide (Bellard et al., 2012; IPCC, 2014). There is an urgent
46 need to document the impacts of climate change that have already happened in order to
47 improve our ability to predict their future impacts on natural systems. There is growing
48 evidence for distribution shifts and phenological change (Parmesan and Yohe, 2003; Chen et
49 al., 2011), and of impacts on ecological communities and species' populations (Devictor et
50 al., 2012; Oliver et al., 2017), leading to potential disruption in biotic interactions (Cahill et
51 al., 2013; Ockendon et al., 2014). However, there remain significant gaps in our
52 understanding of the climate change influence on population abundances of specific species
53 over time, and the traits associated with vulnerability to such impacts. To narrow this gap in
54 knowledge, we present a detailed analysis of the response of over 300 UK butterfly and moth
55 species to climate change.

56 Due to their sensitivity to temperature and good data availability, UK butterflies and moths
57 are a suitable model group to investigate climate change impacts. They are well monitored,
58 with documented range expansions (Warren et al., 2001; Mason et al., 2015), phenological
59 changes (Thackeray et al., 2010, 2016) and sensitivity to variation in the weather (Roy et al.,
60 2001; WallisDeVries et al., 2011; Mair et al., 2012; McDermott Long et al., 2017). Recent
61 work has also suggested that climate change, amongst other drivers, has caused long-term
62 declines in moth populations (Fox, 2013; Martay et al., 2017), but has not identified how this
63 impact varies between species. As well as containing many species of conservation concern
64 (Fox et al., 2013, 2015) moths are also an important group from an economic and ecosystem
65 service provision perspective, including a number of agricultural and horticultural pests (Ellis
66 et al., 2015). They are a keystone group for community function, acting as pollinators for

67 many flowering plants (Hahn and Brühl, 2016), and as important prey for other taxa, such as
68 culturally significant bird and bat species (Krištín and Patočka, 1997).

69 There is increasing interest in the ecological traits associated with species' vulnerability to
70 climate change, as a means of identifying future conservation priorities (e.g. Foden and
71 Young, 2016). However, evidence to identify the species' characteristics impacted by climate
72 change is generally lacking (Wheatley et al., 2017), or available only for a limited number of
73 taxa (e.g. Pearson et al., 2014; Pacifici et al., 2017). In particular, there is little information to
74 identify the traits of invertebrate species affected by climate change. As our sample of
75 butterflies and moths include a wide range of species from habitat specialists to generalists,
76 sedentary to mobile, southern to northern (at a national scale), this analysis provides an
77 important opportunity to assess the traits associated with vulnerability to climate change
78 impacts that may be relevant to other taxa.

79 In order to document climate change impacts on butterflies and moths, we examine the extent
80 to which variation in population growth rates can be explained by temperature and
81 precipitation, key variables which cover the majority of climate change impacts on terrestrial
82 species (Pearce-Higgins et al., 2015b). First we model annual population changes from the
83 mid-1970s to 2011 as a function of annual fluctuations in these weather variables, whilst also
84 accounting for non-climatic trends in abundance through time. This analysis is best regarded
85 as summarising impacts of annual variation in the weather upon the abundance of flying
86 adults. Next we consider the extent to which these models can be used to explain long-term
87 trends in abundance between decades, as this will show whether the impact of climate change
88 increases over time (Eglinton and Pearce-Higgins, 2012). Finally, we relate inter-specific
89 differences in those responses to various ecological traits.

90 In doing so, we are able to test several key hypotheses for Lepidoptera, with more wide-
91 ranging data than before:

- 92 1. That annual fluctuations in butterfly and moth populations are largely driven by weather
93 (Roy et al., 2001).
- 94 2. That climate change impacts vary between seasons (Martay et al., 2016).
- 95 3. That extreme weather events will exert a disproportionate impact on populations
96 compared to more typical weather fluctuations (Oliver et al., 2015).
- 97 4. That long-term population trends are largely driven by climate change, the impacts of
98 which have increased through time (Martay et al., 2017).
- 99 5. That climate change impacts are more negative for habitat specialists, but positive for
100 habitat generalists (Davey et al., 2012)
- 101 6. That climate change impacts are negative for northerly distributed species, but are
102 positive for southern species (Devictor et al., 2012).
- 103 7. That climate change impacts vary with species' life-history (McDermott Long et al.,
104 2017).

105

106 **2. Materials and Methods**

107 *2.1. Butterfly and moth abundance indices*

108 Butterfly data were derived from the UK Butterfly Monitoring Scheme (BMS), in which
109 volunteer recorders count butterflies along fixed-transects each week (where possible) from
110 April through to September, within set weather criteria (Pollard and Yates, 1993). The
111 scheme has grown incrementally from its inception in 1976 to cover more than 1000 sites by
112 2011 (Botham et al., 2013). In early years of the scheme, recording was restricted almost
113 entirely to England so we therefore restricted our analysis to data from England, the most
114 evenly recorded country (Martay et al., 2016).

115 Moth data were derived from the Rothamsted network of light traps run by a mix of
116 professionals and volunteers on a daily basis from 1975 (Woiwod and Gould, 2008). Here,
117 analysis was restricted to the 13 sites from across the UK with a continuous data run to 2010,
118 thus eliminating the need to account for spatial variation in coverage through time (Martay et
119 al., 2016).

120 Firstly, we generated annual abundance indices for each species at each site, accounting for
121 missing weekly counts in the case of butterflies (Roy et al., 2001). Because we were
122 interested in large-scale responses to climate, secondly, we collated these into annual multi-
123 site indices of population change for each species ($u_{i,y}$ in year Y for species i), using the
124 freeware program TRIM, a widely used method to document national trends (e.g. Pannekoek
125 and van Strien, 1998; Conrad et al., 2004). Species for which there were no records in any
126 one year were excluded. Sufficient data were available for analysis of 55 butterfly species
127 and 265 moth species.

128 2.2. Weather variables

129 We used UK Met Office 5km gridded datasets, averaged across England and the UK for
130 butterflies and moths respectively (Perry and Hollis, 2005), to calculate average mean daily
131 temperature and seasonally summed precipitation, separately for winter (Dec-Feb), spring
132 (Mar-May), summer (Jun-Aug) and autumn (Sept-Nov). Given the potential for these
133 variables to operate on populations through lagged effects (e.g. Pearce-Higgins et al., 2015a),
134 we considered the 24 months preceding the season in which the last flight of a species was
135 recorded; giving a total of 16 variables (2 variables calculated separately for each of the 8
136 seasons in the 2 years preceding the flight period). Thus for adults of species such as the
137 Small Blue (*Cupido minimus*) which are active from May to August, we used data from
138 summer in year_t to autumn in year_{t-2}. We refer to these variables describing annual variation

Commented [EBD1]: Is there a reason why butterflies were to 2011 and moths to 2010?
BM: Data beyond 2010 was not available for moths

139 in seasonal temperature and precipitation values as weather variables (V_w), but use climate to
140 refer to decadal averages or change over longer time-periods. We tested whether there were
141 trends in these mean seasonal weather variables throughout the study area (England for
142 butterflies and UK for moths) between 1975 and 2010 using GLMs.

143 2.3. Models of population growth

144 Population growth was described by $\Delta n_{\theta_i, Y} = \log(n_{\theta_i, Y} / n_{\theta_i, Y-1})$, where $n_{\theta_i, Y}$ is the observed
145 annual national population index in year Y for species θ_i . We modelled population growth as
146 a function of weather variables $f(V_w)$ for each species as follows (Model 1).

$$147 \quad \Delta n_{\theta_i, Y} = \alpha + b_0 n_{\theta_i, Y-1} + b_1 Y + f(V_w) \quad \text{Model 1}$$

148 Count in the previous year ($n_{\theta_i, Y-1}$) was included to account for potential density-
149 dependence (Pearce-Higgins et al., 2015a), known to be important for some butterfly and
150 moth species (Roy et al., 2001). Year was included to account for potential non-climatic
151 drivers of long-term trends which could alter the population growth rate through time. Given
152 the potential for non-linear relationships to occur between population growth and both
153 weather variables (indicating disproportionate impacts of extreme weather events) and year,
154 we also considered quadratic terms in cases where they were shown in preliminary analysis to
155 have significant explanatory power when added to a model of population growth as a
156 function of the related linear weather variable, year and count in the previous year. Quadratic
157 terms were only included in combination with the associated linear term. Given the sample
158 size of 35 years for both groups, population growth was modelled as a function of up to six
159 variables (two of which were always count in the previous year and year), to reduce the risk
160 of over-fitting.

161 All possible models were fitted using the lm function in R (R Core Team, 2015) and model
162 selection was undertaken by Akaike information criterion corrected for small sample sizes
163 (AICc; Anderson, 2007), using the dredge function from the MuMIn package (Barton, 2016)
164 in R, selecting the best-fitting of the candidate models. We tested for multicollinearity
165 between the variables in resulting models by examining whether the Pearson correlation
166 coefficients $r > 0.7$, the threshold considered necessary to prevent reliable model estimation
167 (Dormann et al., 2013). For only six of the 320 species was this threshold exceeded, and for
168 each of these species the collinearity was between the year term and the count in the previous
169 year. As very few species were affected, this should have a minimal impact on the results.

170 Model fit was assessed by r^2 . Hierarchical partitioning (Chevan and Sutherland, 1991; Walsh
171 and Mac Nally, 2013) was used to identify the proportion of the variance which could be
172 attributed specifically to the weather variables (V_w). The product of r^2 and V_w gave the r^2
173 attributable to annual variation in the weather (sensitivity), used to test Hypothesis 1 (that
174 annual fluctuations in butterfly and moth populations are largely driven by weather). We used
175 t-tests to determine whether the r^2 or sensitivity differed between butterflies and moths after
176 checking for normality.

177 To test Hypothesis 2 (that climate change impacts vary between seasons), we identified how
178 many times each weather variable was included in the models (in each case indicating a
179 significant relationship between the weather variable and the species' population growth)
180 from the best-fitting model for each species, and whether these were positive or negative. The
181 direction of quadratic relationships was determined by plotting their form over the range of
182 the climatic data. We used Pearson's chi-squared test to test whether each of the 24 weather
183 variables had notably positive or negative impacts across species (separating moths and
184 butterflies), after applying a Bonferroni correction. The prevalence of significant quadratic
185 relationships indicated the extent to which extreme events had a disproportionate impact on

186 populations, as described by non-linear relationships between weather variables and
187 population growth (Hypothesis 3).

188 2.4. Models of population trends

189 By predicting population growth using Model 1 and observed weather variables, we were
190 able to test the extent to which observed long-term trends were consistent with the cumulative
191 impact of modelled effects of annual variation in weather upon population growth. Thus, for
192 each species in each year we predicted the weather-driven population growth ($\Delta n_{Vw_i,Y}$) as a
193 function of the observed relevant weather variables (Vw) using the best fitting models
194 (described above). In these predictions we fixed the year terms to equal the first year in the
195 time-series (Y_1), thus removing the impact of variation in non-climatic drivers of change. To
196 predict this weather-related population growth between the first and second year only,
197 observed population count in the first year was used but thereafter the predicted count in the
198 previous year ($n_{Vw_i,Y-1}$) was used to predict the population growth in the following year,
199 ensuring that the model was ‘free-running’ (Model 2; see Eglington and Pearce-Higgins,
200 2012).

$$201 \quad \Delta n_{Vw_i,Y} = \alpha + b_0 n_{Vw_i,Y-1} + b_1 Y_1 + f(Vw) \quad \text{Model 2}$$

202 In this prediction, annual growth rates ($\Delta n_{Vw_i,Y}$) were therefore determined by the effects of
203 density-dependence, weather and an underlying population growth rate (due to year being
204 included in the model, representing linear non-weather related change). Long-term trends
205 were quantified from the slope of the observed and weather-model predicted population
206 estimates through time as a measure of overall change across the study period which we refer
207 to as β_i and β_{Vw_i} , for species i . By modelling β_i as a function of β_{Vw_i} , taxa and the interaction
208 between taxa and β_{Vw_i} , we tested whether the long-term population trends were consistent
209 with expected effects of climate change (Hypothesis 4).

210 Based on observed population trends (β_i), species were classified by the extent to which their
211 population trends were increasing (statistically significant ($P < 0.05$) positive linear trend),
212 decreasing (significant negative linear trend) or stable (non-significant linear trend). We then
213 used the same criteria to determine the extent to which each species' population trend had
214 been influenced by trends in the weather variables, based on the slope of the weather-model
215 prediction through the time-series (β_{vw_i}). We used tests of equal proportions to test whether
216 within each taxon there are significant differences in the number of species with declining
217 observed and weather-model predicted trends compared to increasing trends. The
218 combination of observed trends and weather-model prediction trends was used to categorise
219 species by the impact of weather trends upon their population (Table 2).

220 2.5. Traits analysis

221 Butterfly and moth traits were collated from a range of sources and databases (Dennis et al.,
222 2005; Waring and Townsend, 2009; Dennis, 2010) to cover ecological and life-history
223 parameters that may affect species' sensitivity to weather variables (Table 1). In order for the
224 analyses to be comparable across both groups, which were modelled together, we used trait
225 variables that were available for both butterflies and moths.

226 The influence of traits upon sensitivity (proportion of variance which could be attributed to
227 weather variables) and the weather-model prediction trend (β_{vw_i}) was tested to identify how
228 variation in the importance of weather in driving population fluctuations and long-term trends
229 varies between groups of species. Both responses were modelled as a function of the trait
230 variables in Table 1. Given multiple habitat associations for many species, habitat category
231 was separated into species that occur in woodland (D1), unimproved grassland (D2) and
232 upland (D3) categories, the main associations of habitat specialists, and multiple associations
233 were possible for each species. Linear mixed models were fitted in R (R Core Team, 2015)

234 using the lme4 package (Bates and Maechler, 2010), with random factors for family, genus
235 and taxa to account for phylogenetic correlation. Model selection was undertaken by AICc
236 using the dredge function within the MuMIn package in R, allowing for up to five variables,
237 in addition to the random factors. This analysis allowed us to test Hypotheses 5 – 7.

238 2.6. Impacts of climate change

239 Annual fluctuations in population growth for each species could be highly dependent on the
240 weather, irrespective of the long-term impact of climatic trends. To better separate these
241 fluctuations from the long-term impacts of changes in weather variables (climate change)
242 upon overall butterfly and moth abundance, we examined the change in mean observed and
243 weather-model predictions of population abundance between three decades for each species
244 e.g. (Models 3 & 4).

$$245 \Delta n_{i,90s - 80s} = \log(\overline{n_{i,Y = 1990:1999}} / \overline{n_{i,Y = 1980:1989}})$$

246 *Model 3*

$$247 \Delta n_{vw_i,90s - 80s} = \log(\overline{n_{vw_i,Y = 1990:1999}} / \overline{n_{vw_i,Y = 1980:1989}})$$

248 *Model 4*

249 This focus on decadal means from 1981-2010 is complementary to our analyses of long-term
250 trends, but avoided the results being overly influenced by extreme weather events at the start
251 and end of the time-series; 1976 was characterised by summer drought, whilst the 2010/11
252 winter was extremely cold (Palmer et al., 2017).

253 Specifically, we tested for whether the decadal changes in mean population estimates (e.g.

254 $\Delta n_{iO,90s - 80s}$) were significantly different from zero and whether they varied between- taxa.

255 We also tested whether the observed decadal population changes for each species (e.g.

256 $\Delta n_{iO,90s - 80s}$) correlated with weather-model predicted changes (e.g. $\Delta n_{vw_iO,90s - 80s}$)

Commented [EBD2]: I'm not sure I understand this, unless it should be $n_{O,Y=1980:1989}$?

BM: Yes, that should be no,Y=1980:1989

257 and whether this varied between taxa. These analyses allowed us to test whether there were
258 climate change impacts on long-term population trends and whether the climate change
259 impacts increased over time (Hypothesis 4). This final analysis was undertaken in SAS 9.4
260 using PROC MIXED, applying a Kenward-Rogers correction for the degrees of freedom.

261 Unless specified, means are presented with standard errors throughout.

Trait	Definition
A. UK latitudinal distribution	Simplified to four categories based on occurrence within 100km latitudinal band; 1 = southerly – occurring up to 300km north (the Wash), 2 = occurring up to 500km north (Cumbria / N. Yorkshire), 3 = occurring up to 600km north (Northumberland and southern Scotland), 4 = occurring to 1000km north or higher, virtually or totally throughout whole of UK.
B. type of main larval food plants	1 = deciduous trees, including low deciduous in hedgerows (Hawthorn etc), 2 = coniferous trees and shrubs, 3 = grasses, including sedges and rushes, 4 = dicots, including herbaceous and low woody shrubs such as heather etc. 5 = lichens, mosses, fungi and algae (majority are lichens), -6 = polyphagous (covering at least two of the above categories).
C. Broad categories of larval feeding specialisation	1 = monophagous (one species only or rarely other species), 2 = specialist (restricted to one family of food plant or lower taxa of plants apart from food resources rarely taken), 3 = intermediate generalist (restricted to one main larval food plant group), 4 = polyphagous (spanning at least two main larval food plant groups).
D. Broad habitat preferences	D1 = woodland, D2 = unimproved grassland (inc. downland), D3 = upland – each a binary term.
E. Wing span in mm	mean width of the span of the forewings (as surrogate for dispersal power, Sekar, 2011)
F. Overwintering	1 = egg, 2 = larva, 3 = pupa, 4 = adult, 5 = migrant

stage

- G. Voltinism 1 = always univoltine, 2 = variable between one to two (rarely three) generations, with multiple generations in the south and single generations further north, 3 = obligate multivoltine with two generations per year, 4 = obligate multivoltine, with three generations per year.
- H. Flight period 1 = spring (March to May), 2 = summer (June to August), 3 = spring and summer (March to August), 4 = autumn (September to November), 5 = summer and autumn (June to November), 6 = spring, summer and autumn (March to November), 7 = autumn, winter and spring (September to May) and (rarely) all year round
- I. Larval period I1 = January to March, I2 = April to June, I3 = July to September, I4 = October to December – each a binary term such that larval periods can span multiple seasons.
- J. Pest species Binary term denoting if the species is regarded as an agricultural or horticultural pest.
- K. Priority Species for Conservation Binary term defining if a species is defined as ‘conservation priority species’ by formal Governmental processes prior to 2012 (Eaton et al., 2015)
- L. Larval start month Initial month for the larval stage.
-

264 **Table 2.** Categorisation of the impact of weather trends on species according to the cross-
 265 tabulation of observed population trends and weather prediction trends.

		Observed population trend		
		Decreasing	Stable	Increasing
Weather prediction trend	Decreasing	Loser Significant population decline matches weather prediction trend.	Hindered Population trend constrained by decreasing weather prediction trend.	Hindered Population trend constrained by decreasing weather prediction trend.
	Stable	Unaffected Stable weather prediction trend.	Unaffected Stable weather prediction trend.	Unaffected Stable weather prediction trend.
	Increasing	Helped Population trend ameliorated by increasing weather prediction trend.	Helped Population trend ameliorated by increasing weather prediction trend.	Winner Significant population increase matches weather prediction trend.

266

267 **3. Results**

268 *3.1. Weather variables*

269 Throughout the study area (England for butterflies and UK for moths) the mean seasonal
270 temperatures increased significantly between 1975 and 2010 except for winter temperature
271 ([Supplementary material](#), Appendix [AS1](#)). Precipitation did not vary over time in any season
272 except for an increase in summer rain across the UK ([Supplementary material](#), Appendix
273 [S1A](#)). Mean annual temperatures increased between decades by 0.49 ± 0.10 °C/decade ($P <$
274 0.001) with the UK mean annual temperature in the 1980s, 1990s and 2000s respectively 8.4,
275 8.9 and 9.3 °C.

276 *3.2. Models of population growth*

277 The best-fitting models of population growth (Model 1) explained between 29.9% and 89.5%
278 of the variation in observed populations (r^2) across both butterflies and moths ([Supplementary](#)
279 [material](#), Appendix [BS2](#)). There was a significant difference in the proportion of variation
280 explained between butterflies (67.6%) and moths (63.8%; $t = 2.739$, $P = 0.007$). The
281 proportion of this variation that could be attributed to weather variables (V_w) suggests annual
282 variation in weather alone explained a mean of 28.8% of the variation in population growth
283 across all species (ranging from 0% - 65.0% for individual species) (Hypothesis 1). This
284 proportion did not differ significantly between butterflies and moths ($t = -0.588$, $P = 0.558$).
285 Eleven weather variables were found to affect population growth rates in significantly more
286 species than the 1/20 expected by chance (Fig. 1) (Hypothesis 2). The most widespread
287 impact of weather was a significant positive association between population growth rate and
288 summer_t temperature, found in 35% of butterflies and 44% of moth species. However,
289 significant negative effects of temperature were apparent at other times of the year, with the
290 growth rates of 29% of butterfly species negatively correlated with winter_{t-1/t} temperature and
291 population growth rates of 17%, 23% and 19% of moths species negatively correlated with

292 summer_{t-1}, winter_{t-1/t} and spring_t temperature respectively. Moth population growth was
293 significantly negatively associated with rainfall throughout the year, affecting 21% of species
294 in autumn_{t-1}, 16% in winter_{t-1/t}, 17% in spring_t and 14% of species in summer_t, whilst
295 population growth rates of 27% of butterfly species was negatively associated with autumn_{t-1}
296 rainfall.

297 Only 9% of significant relationships with weather variables were quadratic (Hypothesis 3).
298 These relationships comprised more than 5% of the possible relationships in any season
299 expected by chance for butterfly population responses to summer_t temperature alone. In this
300 instance only 4 species (*Hamearis luci*, *Pyronia tithonus*, *Thymelicus sylvestris*, *Lasiommata*
301 *megara*) showed quadratic negative relationships indicative of extreme negative responses to
302 summer_t temperature.

303 3.3. Models of population trends

304 There was no overall relationship between observed trends (β_i) and weather-model predicted
305 trends (β_{vw_i}) ($F_{1,317} = 0.31$, $P = 0.58$), or any difference in this relationship between
306 butterflies and moths ($F_{1,316} = 0.06$, $P = 0.80$), although moths exhibited more negative
307 population trends than butterflies ($F_{1,317} = 9.64$, $P = 0.0021$). Cross-species trends across all
308 species were not therefore strongly related to weather-model predicted trends across 35 years.
309 Likewise, there were more moths with significantly declining population trends than
310 increasing ($\chi = 40.1$, $P < 0.001$) but no difference in the proportion of moth species with
311 increasing and declining weather-model predicted trends ($\chi = 0.59$, $P = 0.44$) and no
312 difference in the proportions of butterflies with increasing and declining observed ($\chi = 1.10$,
313 $P = 0.29$) or weather-predicted trends ($\chi = 0.66$, $P = 0.42$). Six species of butterfly and 36
314 species of moth were classified as losers, with a further 10 and 48 respectively classified as
315 hindered (Table 4). These numbers compare with 5 and 9 species respectively classified as

316 winners and 17 and 61 species respectively, classified as helped. The final classification of
317 each species is given in [the supplementary material](#), Appendix [S2B](#). Although long-term
318 trends across all species were not consistently linked to climate change, for a sizeable subset
319 of species, trends were consistent with the modelled expectation of climate change
320 (Hypothesis 4). For observed, modelled and weather-model predicted abundances for all
321 species see [the supplementary material](#), Appendix [S3C](#).

322 *3.4. Traits analysis*

323 The best-fitting model for describing the sensitivity of species' populations to weather by
324 traits showed significant effects of upland habitat association, overwintering strategy and
325 voltinism (Table 3), although combined, these variables only accounted for 9% of the
326 variation between species. Sensitivity was lowest in species occupying upland habitats
327 compared to other habitats. Sensitivity in species overwintering as larvae was greater than in
328 species overwintering as pupae and higher in non-migratory species compared to migratory
329 species (Hypothesis 7). Finally, univoltine species showed the lowest sensitivity to weather
330 variables, particularly compared to species with variable voltinism that were most sensitive.

331 Between-species variation in weather-model prediction trends (β_{vw_i}) varied strongly with
332 UK latitudinal distribution (Hypothesis 6), habitat (Hypothesis 5) and pest status, accounting
333 for 10% of the variance between species (Table 3). The effect of weather on long-term trends
334 was most positive in the most southerly-distributed species, and most negative in northerly-
335 distributed or widespread species. Species associated with woodland and unimproved
336 grassland habitats showed more positive weather trends than those from other habitats. The
337 modelled effect of weather upon trends was also significantly more positive for pest species
338 than other species.

339 *3.5. Impacts of climate change*

340 Given strong inter-annual fluctuations in butterfly and moth populations which may have
341 influenced the slope of the long-term trends, we regard the impacts of climate change as
342 better assessed from changes in decadal averages (Fig. 2a & b). Between the 1980s and 1990s
343 the mean observed and weather predicted decadal moth abundances remained stable
344 ($\Delta n_{\text{moths},90\text{s}-80\text{s}} = -0.056 \pm 0.031$, $P = 0.074$; $\Delta n_{\text{Vw_moths},90\text{s}-80\text{s}} = 0.037 \pm 0.024$, $P = 0.13$) while
345 observed and decadal butterfly abundances increased by about 4% ($\Delta n_{\text{O_butterflies},90\text{s}-80\text{s}} = 0.037$
346 ± 0.012 , $P = 0.003$) of which about 76% was consistent with the expectation from the
347 weather-model predicted increase ($\Delta n_{\text{Vw_butterflies},90\text{s}-80\text{s}} = 0.028 \pm 0.011$, $P = 0.019$). Between
348 the 1990s and the 2000s moth populations declined by 28% ($\Delta n_{\text{moths},00\text{s}-90\text{s}} = -0.280 \pm 0.032$, P
349 < 0.001), of which about 38% was consistent with the weather-model predicted expectations
350 ($\Delta n_{\text{Vw_moths},00\text{s}-90\text{s}} = -0.108 \pm 0.022$, $P < 0.001$), indicating the contribution that climate change
351 may have made to the decline (Hypothesis 4). Between the 1990s and 2000s butterfly
352 populations were largely stable ($\Delta n_{\text{butterflies},00\text{s}-90\text{s}} = -0.026 \pm 0.014$, $P = 0.065$; $\Delta n_{\text{Vw_butterflies},00\text{s}-$
353 $90\text{s}} = -0.010 \pm 0.009$, $P = 0.306$) (Fig. 2c).

354 There was a significant correlation between observed and weather-predicted species-specific
355 differences in abundance between the 1980s and 1990s (respectively $\Delta n_{i,90\text{s}-80\text{s}}$ and $\Delta n_{\text{Vw}_i,90\text{s}-$
356 $80\text{s}}$) ($F_{1,318} = 8.61$, $P < 0.0001$, $r^2 = 0.19$; Fig. 3a), that did not differ significantly between
357 butterflies and moths (taxa * weather-trend interaction, $F_{1,319} = 0.01$, $P = 0.93$; taxa, $F_{1,318} =$
358 0.15 , $P = 0.13$). Between the 1990s and 2000s there was also no difference in the correlation
359 between observed ($\Delta n_{i,00\text{s}-90\text{s}}$) and weather-predicted differences in abundance ($\Delta n_{\text{Vw}_i,00\text{s}-90\text{s}}$)
360 between taxa (taxa * weather-trend interaction, $F_{1,318} < 0.01$, $P = 0.98$), although butterfly
361 population trends were more positive than moths (taxa, $F_{1,318} = 9.24$, $P = 0.0026$) and there
362 was again a strong correlation between observed and weather-predicted trends ($F_{1,318} = 33.06$,
363 $P < 0.0001$, $r^2 = 0.13$; Fig. 3b).

Commented [EBD3]: Are these averages across species? I'm confused as I think the O in $\Delta n_{\text{O},90\text{s}-80\text{s}}$ etc is an index for species but this is for multiple species? Similarly with the other comparisons

BM: hopefully clearer now. I've changed the "o" to "i" as I was getting confused about whether the O was for species or observed.

364 **Table 3.** The results of the traits analysis, presenting the final models for Sensitivity and
 365 Weather trend, where the traits were selected by AICc.

Variable	Parameter estimate	SE
Sensitivity $r^2=0.089$		
Intercept	28.019	1.493
D3 (upland)	-2.746	1.356
F2 (larvae)	2.898	1.823
F3 (pupae)	-1.504	1.909
F4 (adult)	-1.923	4.336
F5 (migrant)	-20.889	6.803
G2 (variable voltinism)	5.519	1.721
G3 (obligate multivoltine 2 generations)	2.454	2.292
G4 (obligate multivoltine 3 generations)	7.391	7.950
Weather trend $r^2=0.101$		
Intercept	0.005	0.006
A UK latitude 2	-0.010	0.006
A UK latitude 3	-0.017	0.007
A UK latitude 4	-0.019	0.006
D1 (woodland)	0.007	0.004
D2 (unimproved grassland)	0.008	0.003
J Pest species	0.009	0.004

366

367

368 **Table 4.** Butterfly and moth population trends and modelled trends from the weather-related
 369 model to indicate the long-term impact of climate change. See methods and Table 2 for
 370 criteria used to categorise species' responses.

Climate response	Weather-related trend	Observed trend	Butterflies	Moths
Winner	Increase	Increase	5	9
Helped	Increase	Stable	11	30
		Decline	6	31
Unaffected	Stable	Increase	4	16
		Stable	9	49
		Decline	4	46
Hindered	Decline	Increase	2	10
		Stable	8	38
Loser	Decline	Decline	6	36

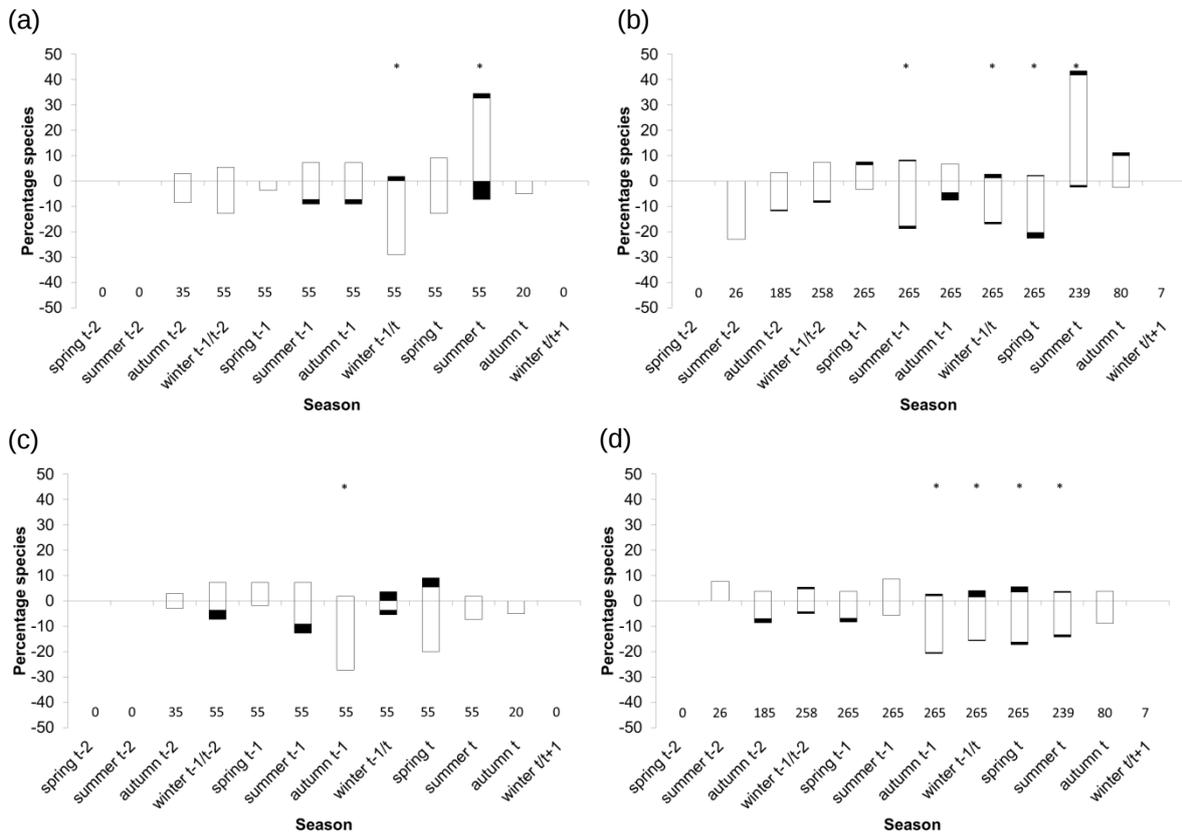
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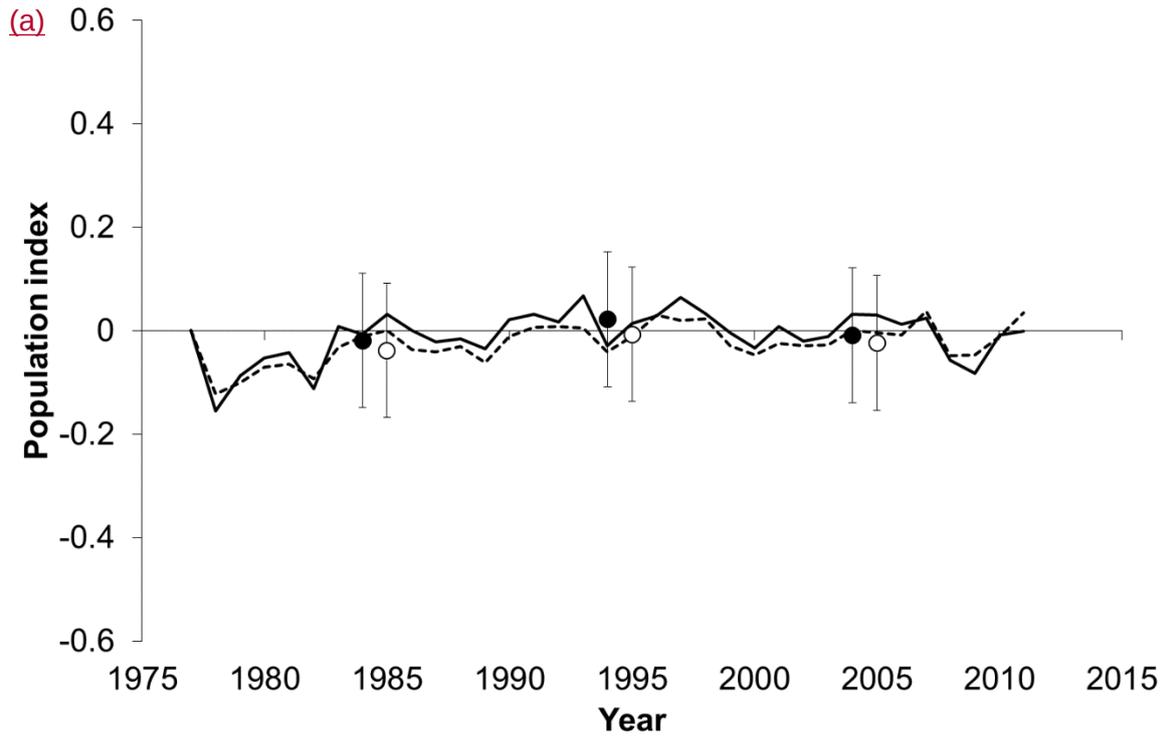
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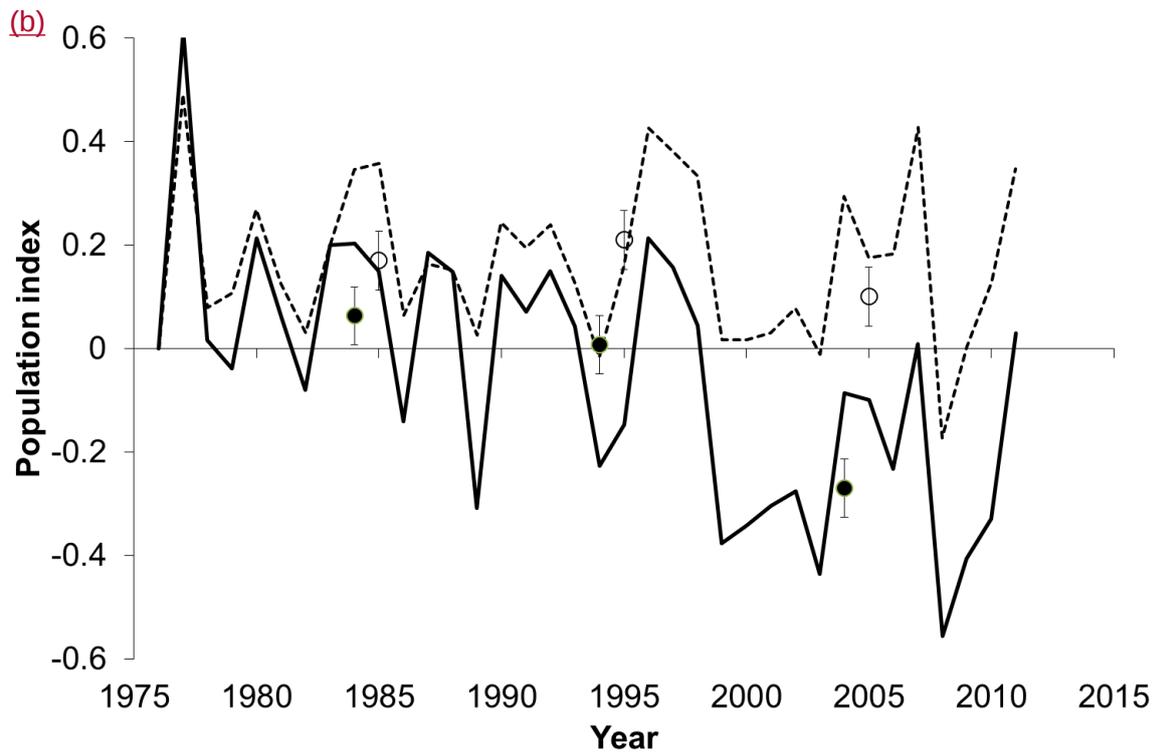
378 **Fig. 1.** Percentage of butterfly (left) and moth (right) species whose population growth rates
 379 correlate with seasonal temperature (top) and rainfall (bottom) variables, from the year in
 380 which the population was monitored ($year_t$) to two years prior to monitoring ($year_{t-2}$). The
 381 percentage of significant positive (above the line) or negative (below the line) relationships is
 382 shown by the open bars. The percentage of significant quadratic relationships with
 383 increasingly positive (above the line) or negative (below the line) relationships is shown by
 384 the black bars. Asterisks identify significant ($P < 0.001$) differences in the frequency of
 385 positive or negative relationships. The numbers under the bars indicate the number of species
 386 for which each variable was tested for; only species active and monitored in winter would
 387 have $winter_{t/t+1}$ (i.e. the winter in which their activity was monitored) included as a potential
 388 variable in their population models.

389

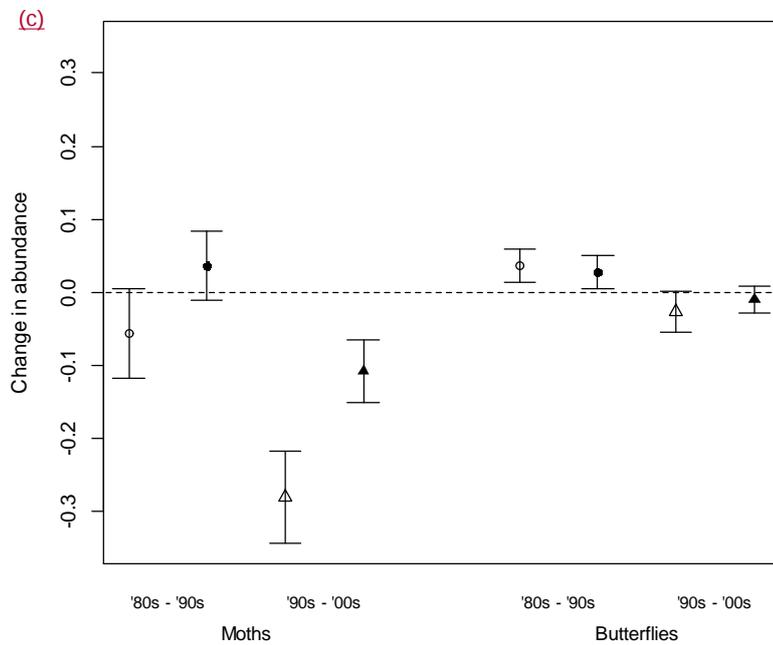
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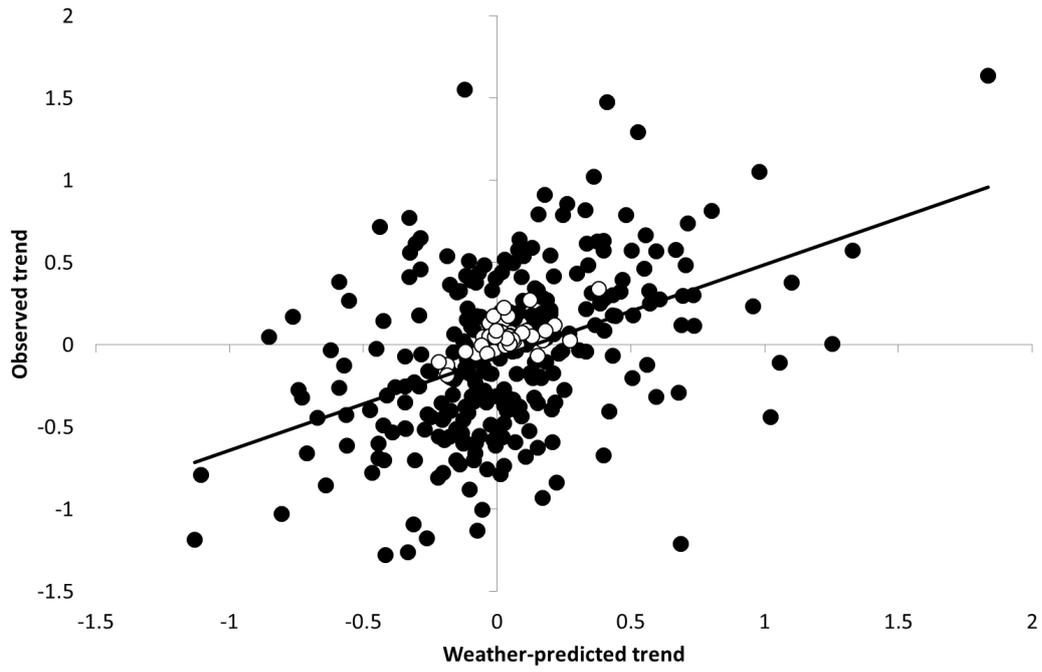


393

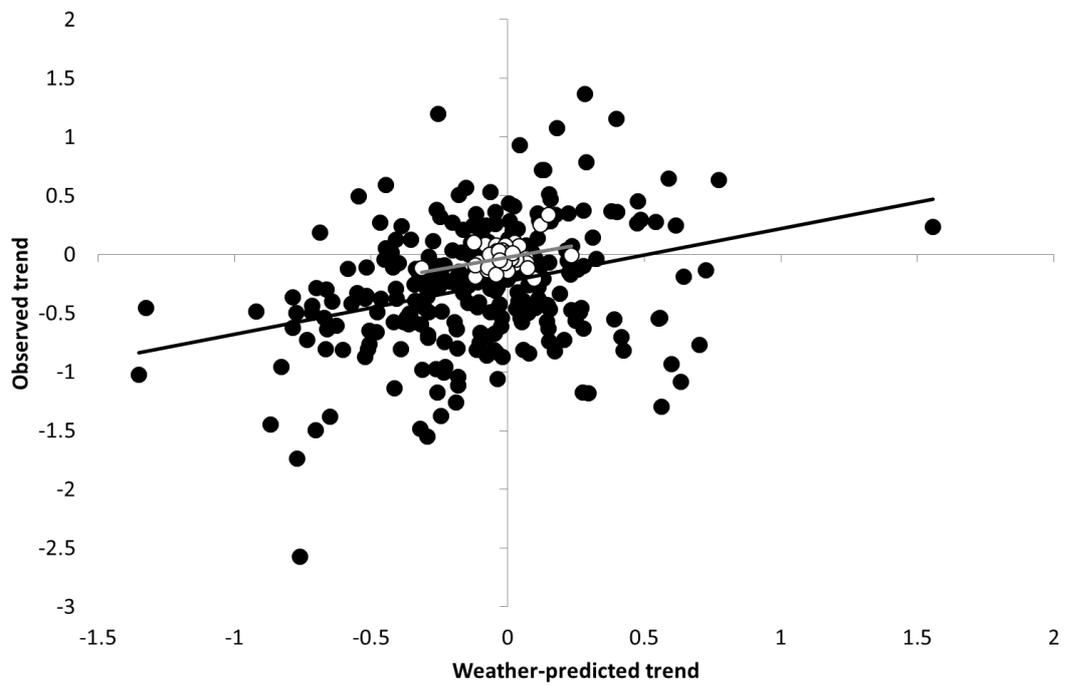
394 **Fig. 2.** (a & b) Multi-species mean observed (solid) and weather-predicted (dotted)
 395 population trends/indices for butterflies (a) and moths (b). Decadal means (\pm s.e.) based on
 396 observed populations (filled) and weather- predictions (open) are shown for the 1980s, 1990s
 397 and 2000s. (c) Change in mean decadal abundance of moths (left side) and butterflies (right
 398 side) from the 1980s to the 1990s (circles) and from the 1990s to the 2000s (triangles).
 399 Observed abundance changes are shown with open symbols (left of pairs) and weather-
 400 predicted changes are shown with closed symbols (right of pairs).

401

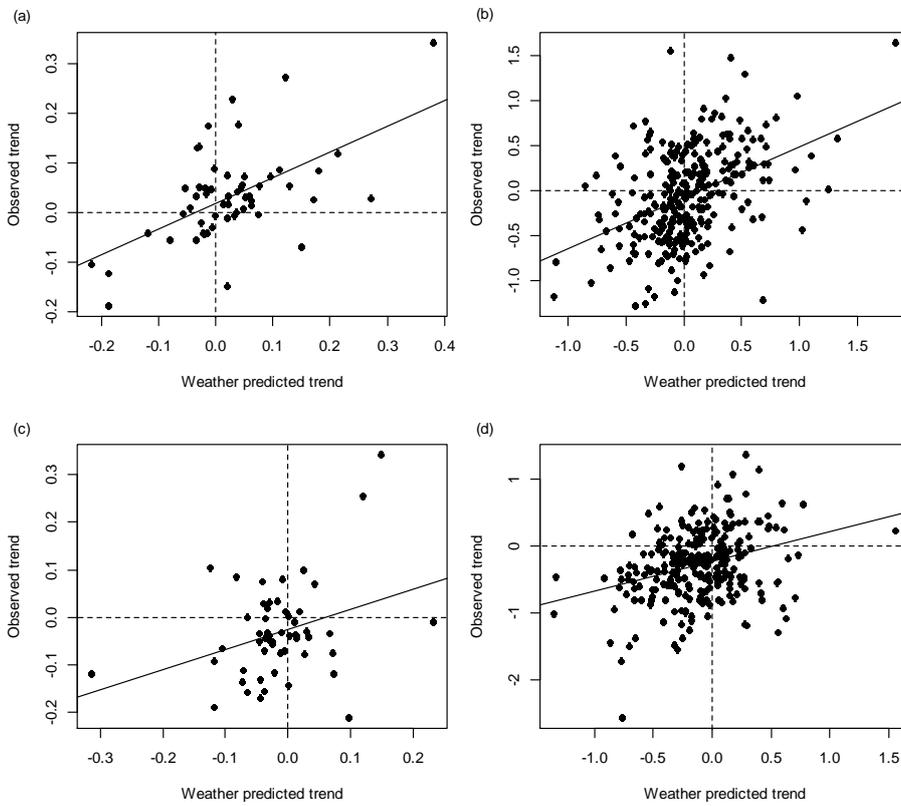
Commented [EBD4]: Aren't these indices rather than trends? Also do we say in the methods how we combine the indices to get multi-species indices?
 BM: You're right – it should be indices. We have removed the methods section on how we calculate the multispecies indices as we don't actually use them for anything except in this fig, and just for visualisation here. The methods for the decadal averages are included though.



402



403



404

405 **Fig. 3.** Correlations between observed and weather-predicted changes in mean abundance
 406 from the 1980s to 1990s (top a & b) and 1990s to 2000s (bottom c & d) for butterflies (a & c)
 407 (open circles and grey line) and moths (filled circles and black line b & d).

Commented [EBD5]: Is there a grey line in the top plot? If so I can't see it! Would it be better to have 4 subplots to separate butterflies and moths?

408 4. Discussion

409 The weather had a strong impact on the national abundance of butterflies and moths,
410 accounting for over a quarter of the annual variation in abundance, and over 50% in 15
411 species (13 moths and 2 butterflies). Using information about the weather over the preceding
412 two years, we can therefore model population growth rates of many species with a reasonably
413 high degree of confidence, providing support for hypothesis 1.

414 Despite this, the evidence in support of hypothesis 4, that long-term population trends are
415 driven largely by climate change, was more equivocal. From the 1980s to the 1990s there was
416 no consistent effect of weather on overall UK moth populations while butterfly populations
417 marginally benefitted from weather changes. However, between the 1990s and the 2000s,
418 climate change (as measured by the contribution of weather to population growth rates and
419 abundances between decades) contributed to a significant decline in overall moth abundance.
420 Over the length of the time-series, climate change had a significant negative effect on 32% of
421 moth species and 29% of butterflies. A greater proportion of butterflies were classified as
422 climate change winners or helped (40%), but there were fewer moths (26%) in this category.
423 Despite a lack of correlation between observed and weather-predicted trends across the entire
424 time-series, there was a significant correlation between weather-predicted and observed mean
425 abundances between both the 1980s and 1990s, and 1990s and 2000s. Given the weather-
426 predicted trends are based upon free-running models, these findings suggest that across a 35-
427 year timescale, error can propagate to reduce their predictive power, particularly given the
428 stochastic nature of butterfly and moth populations which can make long-term trends
429 sensitive to rapid changes in abundance. However, the significant relationships between
430 observed and predicted changes in abundances between decades, and the modelled impact on
431 moth population growth rates and abundances, particularly in the 2000s, indicate that climate
432 change has probably reduced the abundance of many moth population during this period, and

433 therefore contributed to the previously observed decline in moth populations (Conrad et al.,
434 2004, 2006).

435 Research comparing climate and habitat change impacts on UK butterflies between 1977 and
436 2007 concluded that habitat factors were the main driver of change (Oliver et al., 2012). Our
437 results are consistent with this finding. Moth declines have previously been attributed to both
438 habitat changes in the agriculturally intensive lowlands (Fox et al., 2014) and climate change
439 (Martay et al., 2017), which again, our results support. We estimate that about 40% of the
440 moth decline from the 1990s to 2000s could be attributed to climate change as modelled by
441 weather-related population trends, and 60% is therefore potentially due to other factors.
442 Although moth populations are being driven by multiple factors, climate change appears to be
443 a significant driver of change, particularly given their sensitivity to annual changes in the
444 weather. The fact that the magnitude of impact increased in the most recent decade is
445 consistent with the hypothesis of increasing impacts of climate change through time
446 (hypothesis 4).

447 Although 40% of butterflies were predicted to have benefitted from climate change, fewer
448 than 10% of species were clear winners with increasing populations matching weather-
449 modelled trends. Of 18 butterfly species which have shown poleward range expansions over
450 the sampling period attributable to climate warming (Fox et al., 2006), we identified only two
451 of these as ‘winners’ with substantial population level increases (*Aphantopus hyperantus* and
452 *Erebia aethiops*). There is a close link between the rate of population change and range
453 expansion in butterflies, with evidence of declining abundance trends from the mid-1990s to
454 2009 limiting further range expansion (Mair et al., 2014). The weaker relationship between
455 weather-predicted trends and observed trends from the 1990s to 2000s, compared to the
456 1980s to 1990s, suggests that many of the population increases and range expansions of the
457 1980s and 1990s could have been mediated by climate change, but that since then, other

458 processes have become more important and limited continued increase and expansion. The
459 ability of many butterflies to expand their distribution in response to warming is also limited
460 by habitat availability (Warren et al., 2001; Oliver et al., 2012; Mair et al., 2014).

461 Sensitivity to weather was greatest in species which overwintered as larvae and were multi-
462 voltine, but was lowest in migratory and upland species. Unsurprisingly, migratory species
463 had low sensitivity to weather, as we did not include weather variables from their wintering
464 grounds and migratory routes in the models. Low sensitivity to weather in upland species was
465 surprising given previously identified vulnerabilities of some mountain butterflies to climate
466 change (Franco et al., 2006), but could reflect a high availability of temperature ranges over
467 small distances due to altitudinal gradients and microhabitats on mountainous ground.

468 Alternatively, it may be a function of the greater uncertainty associated with the estimated
469 population indices in such species, due to low monitoring coverage in uplands.

470 The sensitivity of species overwintering as larvae indicates that the negative impacts of
471 winter warming are likely to be most important for these species, through the mechanisms of
472 fungal or pathogenic attack, increased energy loss or mismatch, as described below. Multi-
473 voltine species were more sensitive to weather than univoltine species but did not have
474 increased weather-modelled population trends, suggesting that increasing generations per
475 year will benefit some species, but drive declines in others. Increasing temperature can drive
476 declines in multi-voltine species due to a disruption in synchrony with plant host species
477 (Altermatt, 2010).

478 Weather-modelled population trends were most positive for southerly distributed species,
479 providing support for hypothesis 6, and suggesting that climate change is likely to have
480 played a part in facilitating the long-term northwards expansion of many butterfly and moth
481 species (Warren et al., 2001; Mason et al., 2015). This is also consistent with previous

482 analyses of butterfly trends across the UK and Europe indicating that species associated with
483 warmer temperatures have increased in abundance relative to cold-associated species
484 (Devictor et al., 2012; Oliver et al., 2017). In an analysis of UK moth communities across a
485 gradient of long-term monitoring sites, northern and upland species declined in warmer years
486 more than southerly-distributed species (Martay et al., 2016). Weather-modelled trends were
487 more positive for species associated with woodland and unimproved grassland habitats. This
488 supports previous work suggesting that semi-natural habitats may increase resilience to
489 climate change (Oliver et al., 2015, 2017), although runs counter to the previous finding for
490 birds (Davey et al., 2012), that impacts of climate change are more negative for habitat
491 specialists compared to generalists (hypothesis 5). The predicted impacts of weather trends
492 were also more positive for pest species than other species, indicating that climate change
493 may play a role in driving population increases of agricultural and horticultural pests, which
494 may be more adaptable to climate change (Cannon, 1998). Alternatively, many such species
495 are also migratory, and therefore in warm years, UK populations may be boosted by
496 immigration from continental Europe. There was therefore evidence across measures of both
497 sensitivity and weather-modelled population trends that climate change impacts will vary
498 with species' life-history traits (hypothesis 7), although actually the strength of such effects
499 may be fairly limited.

500 The response of species to temperature and precipitation varied widely between seasons,
501 strongly supporting hypothesis 2. Effects of temperature were consistently positive during the
502 summer_t for both butterflies and moths, but were negative during the winter_t and for moths,
503 during the spring_t and previous summer_{t-1} as well. Thus, although warm conditions during the
504 summer boosted adult activity and survival, it appears that warming at other times of the year
505 can have a detrimental impact on populations. The positive effects of summer warming on
506 butterflies are well known (Roy et al., 2001; Warren et al., 2001; McDermott Long et al.,

507 2017), but the negative effects of warm winter weather have only recently been documented
508 for butterflies (Dennis et al., 2016; McDermott Long et al., 2017), and are further supported
509 by our analysis. That such conditions may also affect moths, along with more negative
510 impacts of temperature at other times of the year, is a novel finding, but is consistent with the
511 recent finding that overall moth abundance may be sensitive to variation in temperature
512 during summer, winter and spring months (Martay et al., 2016), and previous analyses on
513 *Actia caja* populations in the UK (Conrad et al., 2002).

514 Several potential mechanisms have been suggested to underpin this negative impact of warm
515 winters and springs. It may be mediated through increased fungal attack of overwintering
516 life-stages (Radchuk et al., 2013), increasing metabolic rates over winter, draining energy
517 reserves, and leading to poorer quality adults (Mercader and Scriber, 2008), or earlier
518 emergence, leading to subsequent mismatch with environmental conditions (Wiklund et al.,
519 1996). Negative lagged temperature effects in summer_{t-1} may be related to drought conditions
520 which can affect host plant growth and therefore reproductive success, and have previously
521 been highlighted as being of concern for some butterfly species (Oliver et al., 2013, 2015).

522 Although we did not find a consistent negative impact of summer_{t-1} temperature across
523 butterflies, it is noteworthy that the one species, *Aphantopus hyperantus*, showing a negative
524 quadratic relationship with summer_{t-1} temperature, and therefore most vulnerable to extreme
525 summer temperatures has previously been identified as highly drought sensitive (Oliver et al.,
526 2013). Fifty moth species showed negative relationships between summer_{t-1} temperature and
527 population growth rates, suggesting that they may be even more constrained by hot summer
528 conditions than butterflies. Thus, despite the fact that greater numbers of species tend to
529 exhibit positive relationships between summer_t temperature than negative relationships with
530 summer_{t-1} temperature, some species are clearly sensitive to negative lagged effects of high
531 summer temperatures and may therefore be particularly vulnerable to climate warming

532 ([Supplementary material](#), Appendix [CS2](#)). Negative lagged effects of summer heat have also
533 been identified for various bird species (Pearce-Higgins et al., 2010; Pearce-Higgins et al.,
534 2015a), suggesting more broadly that the ecological impacts of extreme summer heat may be
535 immediately apparent, but manifest only in subsequent years. Conversely, periods of high
536 precipitation from autumn_{t-1} to summer_t were detrimental to many moth species. Whilst
537 immediate negative impacts of summer_t rainfall are probably related to impacts on activity
538 and adult survival, rainfall at other times of the year, particularly in autumn and winter, may
539 promote fungal attack overwinter (Radchuk et al., 2013).

540 Relatively few non-linear relationships were identified. Quadratic relationships with weather
541 variables would be expected if extreme weather events had a disproportionate impact on
542 populations. Whilst as just discussed, there are clearly some species which are sensitive to
543 extreme conditions, such as summer drought (see also Oliver et al., 2013, 2015), our results
544 suggests that it is not the response to those extreme events which have so far driven recent
545 population trends (see also Palmer et al., 2017). Thus, hypothesis 3 is rejected, although
546 given that extreme events are rare within a 35-year time-series, they may still be important in
547 the future.

548 Although we believe that this study is a significant advance in documenting the species-
549 specific climate change impacts on UK Lepidoptera, and estimating the totality of that impact
550 across species, it does have a number of limitations. Firstly, we examined the response of
551 national population trends to nationally-averaged climate data, which may hide climate-
552 change or habitat impacts if a species is increasing in some areas and declining in others. This
553 may also decrease our ability to identify the impact of extreme weather events, especially if
554 they are local events (Oliver et al., 2013). However, our results are broadly consistent with
555 those of McDermott Long et al. (2017), who also identified few responses to extreme events
556 in butterfly populations using local data. Indeed, given the potential for local adaptation in

557 populations to climate (Roy et al., 2015), our national-scale approach may be more
558 appropriate for documenting large-scale climate change impacts. A second drawback is that
559 non-climate factors were characterised by the model intercept, year and a quadratic year term,
560 rather than being modelled directly. Whilst this means that we cannot identify important non-
561 climatic factors, we were able to at least partially account for such effects; the model
562 intercept allowed a constant non-weather model prediction trend to be identified and two
563 terms relating to year allowed a cubic relationship between population abundance and non-
564 climate factors (i.e. a quadratic relationship between population change and non-climate
565 factors). Thus habitat factors that changed over time would be included in the model provided
566 that the fluctuations occurred over a long-term basis, although any influential non-climatic
567 factors that fluctuated annually would not be modelled well using this approach. It is also
568 worth noting that a stable population growth rate contributed to the weather only prediction,
569 which may not always be biologically accurate in some circumstances. Conversely, some
570 variation due to long-term climate change may also have been soaked up by the year terms,
571 wrongly attributing some long-term impacts of climate change to non-weather factors.
572 Despite these limitations, our results generally mirrored previous research into climate
573 change impacts where equivalent studies were available, and the good descriptive power of
574 our models at the national-level is encouraging.

575 To conclude, we have documented that moth and butterfly populations fluctuate strongly in
576 relation to inter-annual variation in weather conditions. These conditions have deteriorated
577 during the 2000s for many moths, leading to a 24% decline in average moth populations,
578 43% of which is consistent with an impact of climate change. This closely matches the
579 estimated 48% contribution of climate change to the decline in moths in the UK from the
580 1970s to 2011 derived independently by Martay et al. (2017) using an ordination approach.
581 This adds to the evidence that climate change has exerted a significant downward pressure on

582 moth populations, although clearly other factors have also contributed significantly to their
583 decline. There was strong interspecific variation in the impacts of climate change with
584 species in both groups having apparently increased in response to climate change, and others
585 having declined. A significant proportion of this inter-specific variation can be attributed to
586 the modelled impact of weather variables through time. Although our trait-based models were
587 only able to account for a limited amount of variation between species, species overwintering
588 as larvae, and multivoltine species, appeared most sensitive to the effects of weather.
589 Southerly-distributed species were those most likely to have benefited from climate change,
590 along with woodland, unimproved grassland and pest species. Climate change is therefore
591 already having a major impact on the abundance of some butterfly and moth species, with
592 potential implications for their conservation. More broadly, it is also leading to a general
593 decline in national moth populations, as previously documented for a single species by
594 Conrad et al. (2002), and by Martay et al. (2017). Given the importance of these species as
595 pollinators, as keystone species within ecosystems and food webs, and in some cases, as
596 agricultural and horticultural pests, these declines have wide implications for ecosystem
597 health and functioning, for natural capital and if they lead to impacts on food production, for
598 human health and wellbeing (Fox et al., 2010). Given projected trends for warmer, wetter
599 winters in the UK due to future climate change (Jenkins et al., 2009), these trends are likely
600 to be exacerbated in the future.

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609 bioscience strategically.

610 **Supplementary data**

611 [Appendix A. Excel spreadsheet of seasonal trends in UK and English temperature and](#)
612 [precipitation between 1976 and 2010.](#)

613 [Appendix B. Excel spreadsheet of species, model coefficients, trends and classification as](#)
614 [presented in Table 4.](#)

615 [Appendix C. Excel spreadsheet of data on observed, full predicted and weather-model](#)
616 [predicted indices, enabling species-specific plots to be produced.](#)

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871 ~~Appendix S1. Excel spreadsheet of seasonal trends in UK and English temperature and~~
872 ~~precipitation between 1976 and 2010.~~

873 ~~Appendix S2. Excel spreadsheet of species, model coefficients, trends and classification~~
874 ~~as presented in Table 4.~~

875 ~~Appendix S3. Excel spreadsheet of data on observed, full predicted and weather model~~
876 ~~predicted trends, enabling species-specific plots to be produced.~~