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# Population responses to observed climate variability across multiple taxa

## Abstract

A major challenge in ecology is to understand how populations are affected by increased climate variability. Here, we assessed the effects of observed climate variability on different taxonomic groups (amphibians, insects, mammals, herbaceous plants and reptiles) by estimating the extent to which interannual variation in the annual population growth rates ( $CV_\lambda$ ) and the absolute value of the long-term population growth rate ( $|\log \lambda|$ ) were associated with short-term climate variability. We used empirical data ( $\geq 20$  consecutive years of annual abundances) from 59 wild populations in the Northern Hemisphere, and quantified variabilities in population growth rates and climate conditions (temperature and precipitation in active and inactive seasons) calculated over a four-year sliding time window. We observed a positive relationship between the variability of growth rate ( $CV_\lambda$ ) and the variability of temperature in the active season across taxa. Moreover,  $|\log \lambda|$  was positively associated with the variability of precipitation in the inactive season. Otherwise, the direction of the relationships between population dynamics and climate variability (if any) depended on the season and taxonomic group in question. Both  $CV_\lambda$  and  $|\log \lambda|$  correlated negatively with species' lifespan, indicating general differences in population dynamics between short-lived and long-lived species that were not related to climate variability. Our results suggest that although temporal variation in population growth rates and the magnitude of long-term population growth rates are partially associated with short-term interannual climate variability, demographic responses to climate fluctuations might still be population-specific rather than taxon-specific, and driven by other factors than the observed climate variability.

**Keywords:** climate variability, demography, lifespan, long-term time series, population dynamics, population growth rate, taxonomic group, timescale

## 23 **Introduction**

24 Global climate change is likely to lead to concomitant changes in climate means, variability, and  
25 extremes, resulting in more variable and unpredictable environments for animal and plant populations.  
26 The consequences of changes in climate means for ecological and evolutionary processes have been  
27 extensively studied during the past few decades, with the general conclusion being that shifts in mean  
28 temperature and precipitation have the ability to alter population fluctuations (reviewed in Walther et al.  
29 2002, Parmesan and Yohe 2003, Oliver and Morecroft 2014). More recently, climate variability (e.g.,  
30 Lawson et al. 2015, Vázquez et al. 2015) and extremes (e.g., Palmer et al. 2017, van de Pol et al. 2017)  
31 have received increasing attention as important factors that can mediate the effects of shifts in climate  
32 means (Vasseur et al. 2014, Lawson et al. 2015). Over the last three decades, variability in regional year-  
33 to-year temperature has changed substantially worldwide. For example, in the Northern Hemisphere,  
34 especially in North America and Europe, variability in temperature increased notably in the 1980s and  
35 1990s (Huntingford et al. 2013) and extreme temperature events are expected to be even more frequent  
36 in the future (IPCC 2014). Moreover, precipitation variability, including precipitation extremes, is  
37 predicted to increase in the warmer future climate (IPCC 2014, Pendergrass et al. 2017). Such interannual  
38 climate variability has the potential to translate into fluctuations in the abundances of wild populations  
39 through changes in individuals' vital rates, such as survival, growth, and fecundity (e.g., van de Pol et al.  
40 2010, Genovart et al. 2013, Jenouvrier et al. 2015). This link between climate variability and population  
41 fluctuations is based on the fact that, for many species, population growth rates are sensitive to shifts not  
42 only in the means of vital rates, but also in their variance (Doak et al. 2005, Morris et al. 2008, Vázquez  
43 et al. 2015). A major aim in ecology is thus to determine how climate variability can affect populations  
44 (Lawson et al. 2015).

45 One way of measuring population fitness is with the long-term population growth rate, which is a  
46 function of annual finite rates of increase (Lewontin and Cohen 1969). Environmental variability is often  
47 assumed to decrease the long-term population growth rate (Lewontin and Cohen 1969, Tuljapurkar  
48 1982), thus being harmful for populations. However, previous theoretical and empirical studies have  
49 shown that an adverse effect of climate variability on the population growth rate is not a foregone  
50 conclusion (Drake 2005, Doak et al. 2005, Koons et al. 2009, Vázquez et al. 2015). Specifically, climate  
51 variability can either increase or decrease the long-term population growth rate depending on a species'  
52 life history and the vital rates affected (Boyce et al. 2006, Lawson et al. 2015, Colchero et al. 2019), as  
53 well as on the mean climatic conditions encountered by the population (Bozinovic et al. 2011, García-  
54 Carreras and Reuman 2013). As an example, lifespan is generally expected to be a good predictor of the  
55 sensitivity of species to climate variability across diverse taxa, with short-lived species showing greater  
56 responses to variations in vital rates than long-lived species are (Morris et al. 2008, Koons et al. 2009,  
57 Dalglish et al. 2010).

58 So far, many studies have explored the effect of climatic variation on populations by theoretically  
59 perturbing vital rates and assuming that all vital rates experience similar proportional changes (e.g.,  
60 Morris et al. 2008, Dalglish et al. 2010, Jonzén et al. 2010, van de Pol et al. 2010, but see e.g., Palmer  
61 et al. 2017). However, such theoretical perturbations may not reflect the actual changes in vital rates.  
62 Instead, a more direct way to assess the consequences of ongoing climate change for wildlife is to  
63 examine the actual responses of wild populations to climate variability. Here, we used data of population  
64 abundances ( $\geq 20$  consecutive years) from 11 countries to investigate the effect of short-term interannual  
65 climate variability on different taxonomic groups (amphibians, insects, mammals, herbaceous plants,  
66 reptiles) based on 59 wild populations belonging to 54 species. We limited the study to terrestrial, non-  
67 migratory species in the Northern Hemisphere (Western Europe and North America), where the timing

68 of climate seasonality for populations is mostly synchronized. We sought to determine which taxonomic  
69 groups (if any) were particularly sensitive to the observed climatic variability. We characterized the  
70 interannual variability in annual population growth rate as coefficient of variation (CV), and interannual  
71 climate variability using average temperature and precipitation in the fall-winter and spring-summer  
72 seasons (the inactive and active seasons, respectively). Although we do not expect that these two climate  
73 variables would be equally important to all taxonomic groups, we consider them biologically meaningful  
74 for the terrestrial species included here (e.g., Post and Stenseth 1999, Deguines et al. 2017, Mills et al.  
75 2017). All variability was quantified within a four-year moving time window. More specifically, we  
76 focused on the relationships between i) climate variability and the temporal variation in the observed  
77 annual population growth rates ( $CV_\lambda$ ), as well as ii) climate variability and the absolute value of the long-  
78 term population growth rate ( $|\log \lambda|$ ). The use of  $|\log \lambda|$  enabled us to assess the magnitude of population  
79 responses to environmental variability regardless of direction because both negative and positive  
80 responses are possible (Lawson et al. 2015). As environmental fluctuations can lead to population  
81 fluctuations (Tuljapurkar 1982), we predicted that we would find a positive relationship between climate  
82 variability and  $CV_\lambda$  (i.e. we predicted to find an environmental signal in population dynamics). However,  
83 because the species included in this comparative study represent diverse life histories, we hypothesized  
84 that the effects of the climate variables considered would vary among taxonomic groups and lifespans.  
85 Particularly, we predicted that  $|\log \lambda|$  would be higher for short-lived species, which have been reported  
86 to be more sensitive to environmental variability than longer-lived species (Morris et al. 2008). As a  
87 consequence, the populations of short-lived species would either decline or increase at a higher rate than  
88 those of longer-lived species relative to climate variability.

## 89 **Methods**

### 90 *Population and climatic data collection*

91 Time series on population abundances (either annual population densities or population counts) were  
92 extracted from two global databases, the NERC Imperial College Global Population Dynamics Database  
93 (GPDD; NERC Centre for Population Biology, 2010) and the Living Planet Index (LPI; Collen et al.,  
94 2009), based on two main criteria. First, demographic data came from non-migratory, terrestrial species  
95 located in the Northern Hemisphere (see Fig. 1) and consisted of at least 20 consecutive years (selected  
96 data were updated when possible using recently published sources; a list of all data sources can be found  
97 in Appendix S1, Table S1.1 in Supporting Information). By restricting our analysis to such long-term  
98 time series, we hoped to have sufficient information to assess relationships between population dynamics  
99 and climate variables (Teller et al. 2016). Second, only wild, unmanaged populations were considered  
100 (e.g., harvest data were removed; see Appendix S1 for further details about criteria). Moreover, we  
101 included a subset of weed data from the Broadbalk experiment (Moss et al. 2004) which consisted of the  
102 annual frequencies of 19 weed species monitored for 21 years between 1991 and 2014 (3 years of data  
103 were missing when the plots were fallowed; see Appendix S1 for details). To find more studies, we also  
104 conducted a literature search in July 2018 in the Web of Science using the following search term  
105 combinations: (population) AND (demograph\*) AND (abundance OR density OR population size OR  
106 number) AND (time series OR monitoring) AND (long-term). This search produced 615 matches, of  
107 which eleven studies met our selection criteria. Overall, a total of 59 population time series were  
108 analyzed; these represented 54 species with different life histories, including 4 amphibian, 6 insect, 20  
109 mammal, 22 herbaceous plant, and 7 reptile populations from 28 locations across Europe and North  
110 America. The mean length of the studies was  $26.2 \pm 8.4$  years, with the study periods ranging from 1939  
111 to 2016. Estimates of species' lifespans were obtained from PanTHERIA (Jones et al. 2009), AnAge  
112 (<http://genomics.senescence.info/species/>), Animal Diversity Web (ADW (<http://animaldiversity.org/>),  
113 Ecoflora (<http://ecoflora.org.uk/>), and peer-reviewed literature.

114 For each study location, we extracted monthly gridded values of two key climate variables - temperature  
115 (degrees Celsius) and precipitation (mm/month) - at a  $0.5^{\circ} \times 0.5^{\circ}$  spatial resolution from the Climatic  
116 Research Unit's time-series datasets (CRU TS; Harris, Jones, Osborn, & Lister, 2014). Both of these  
117 climate variables have been found to affect population dynamics of most of the taxonomic groups  
118 considered here (Post and Stenseth 1999, Deguines et al. 2017, Mills et al. 2017) and therefore, we chose  
119 to use the same climate variables for all taxa. From these climate data, we derived values for the six-  
120 month average of temperature and precipitation for the periods April-September and October-March. In  
121 the Northern Hemisphere, these two periods correspond to the active growing season (spring-summer)  
122 and the non-active season (fall-winter), respectively, with each period reflecting different environmental  
123 conditions. Although less-studied than climatic conditions during the active growing season, changes in  
124 winter climatic conditions can also influence the survival, overwintering success, and performance of  
125 individuals during the following growing season, which can ultimately affect the population growth rate  
126 and its variability (Roland and Matter 2013, Williams et al. 2015).

127

### 128 *Estimating demographic and climate variability*

129 For each time series, we calculated the observed annual population growth rate ( $\lambda$ ) from year  $t$  to year  
130  $t+1$  as  $N_{t+1}/N_t$ , where  $N$  denotes population abundance. For the weeds, annual observations were missing  
131 for three distinct years in each time series and therefore, we adjusted the growth-rate estimates by the  
132 length of the census interval (Morris & Doak, 2002, p. 68). We used the coefficient of variation (CV) as  
133 our measure of temporal variability in annual population growth rates and in the variability of  
134 precipitation to compare the relative amounts of variation across populations and variables that have  
135 different means. For the temporal variability of temperature, an interval scale variable, standard deviation  
136 was used as a metric of variability. The interannual SD of temperature ( $SD_{Temp}$ ) and the interannual CV

137 of precipitation ( $CV_{Prec}$ ) were estimated separately for both active and inactive seasons after detrending  
138 the data for each population to remove variation attributable to a long-term linear trend. The climate  
139 variables were also scaled by population to ease comparison among populations experiencing different  
140 climatic conditions. Moreover, to describe population dynamics in a variable environment and population  
141 responses to climate variability, we calculated the long-term population growth rate ( $\log \lambda$ ) as the  
142 arithmetic mean of the logged annual population growth rates (Morris and Doak 2002) and considered  
143 the absolute values of  $\log \lambda$ . That is, we focused on change in population size regardless of its direction.  
144 Examining  $\log \lambda$  *per se* across multiple species is not informative for our purpose because the direction  
145 of the relationship between climate variability and  $\log \lambda$  varies within species depending on both the  
146 shape of the population response curve and the mean climatic conditions encountered (Lawson et al.  
147 2015). For example, temperature variability enhances the population growth rate of the fruit fly  
148 *Drosophila melanogaster* at a low mean temperature, but decreases it at high mean temperature  
149 (Bozinovic et al. 2016). Consequently, if populations in different taxonomic groups in the present dataset  
150 happened to represent contrasting environmental conditions, negative and positive responses could  
151 cancel each other out, resulting in no overall response when assessed based on  $\log \lambda$ , while this can be  
152 avoided using  $|\log \lambda|$ .

153 We then examined the effects of climatic variability on the variation in the annual population growth  
154 rates ( $CV_{\lambda}$ ) and the absolute value of the long-term population growth rate ( $|\log \lambda|$ ) within a four-year  
155 period (Pearson's correlation coefficient between the two variables:  $r=0.33$ ). The four-year time window  
156 was chosen because a short timescale may better reflect temporal climate variability that is relevant to  
157 populations (when high local variations are more pronounced, e.g., extreme events; van de Pol et al.,  
158 2017). In the present study, the four-year time window enables multiple observations per population,  
159 capturing periods of lower and higher climatic variation during the study period ( $\geq 20$  years) at each  
160 location. For a sliding time window of four years, the starting year was moved forward one year at a time

161 to estimate  $CV_{\lambda}$ ,  $SD_{Temp}$ , and  $CV_{Prec}$ . The coefficient of variation was corrected for bias in small sample  
162 size as following:  $(1 + \frac{1}{4n}) * CV$ , where n refers to the number of records from the time period  
163 considered (e.g., n=4 for the CVs of climatic conditions estimated over the period of four years; Sokal &  
164 Rohlf, 1995). In those few cases where an annual estimate of  $\lambda$  was missing (weed time series), the  
165 climate variables were adjusted to a five-year time period.

166

### 167 *Statistical analysis*

168 To explore whether climate variability explained a significant proportion of variation in  $CV_{\lambda}$  (sqrt-  
169 transformed) or  $|\log \lambda|$  (sqrt-transformed), we fitted linear mixed-effects models by including several  
170 covariates to control for environmental conditions and spatial heterogeneity. For both analyses and for  
171 each season (active and inactive), our full model included  $CV_{Prec}$ ,  $SD_{Temp}$ , taxonomic group (amphibians,  
172 insects, mammals, herbaceous plants, reptiles), species' lifespan (a continuous variable), mean  
173 temperature and mean precipitation (in the active or inactive season), latitude, and longitude as fixed  
174 effects. Moreover, two-way interactions between the climate variabilities and taxonomic group, and  
175 between the climate variabilities and lifespan were also specified (see the full models in Table 1 and  
176 Appendix S2). Population ID was included in all models as a random effect. In all statistical analyses,  
177 the continuous explanatory variables (covariates) were rescaled: they were centralized and standardized  
178 to ease model interpretation. Multicollinearity was checked for all climatic variables calculated in the  
179 active and inactive seasons and for the variables of each full model using the coefficient of correlation  
180 and variance inflation factors (Zuur et al. 2009). We also visually tested for spatial autocorrelation in the  
181 residuals of the linear mixed models (Zuur et al. 2009) and found none. All models included a first-order  
182 autoregressive correlation structure to account for temporal pseudoreplication (see details for model  
183 selection in Appendix S2, Fig. S2.1).

184 For each analysis, model selection was performed based on the Akaike's Information Criterion adjusted  
185 for small sample size (AICc; Burnham & Anderson, 2002). As a general approach, we started model  
186 selection from the full model (see Table S2.1) by testing for all two-way interaction terms, and then used  
187 the most-parsimonious model to test for the main effects. If multiple models were equivalent (i.e.,  $\Delta AICc$   
188  $< 2$ ), we chose the simplest model based on the principle of parsimony (Table 1; see the full model  
189 selection in tables S2.2-S2.5, Appendix S2). To describe the proportion of variance explained by the  
190 fixed factors, we calculated marginal  $R^2$  values from the final simplified models which best inferred our  
191 results (Nakagawa and Schielzeth 2013, Nakagawa et al. 2017). Models were fitted with the *nlme*  
192 package (Bates et al. 2015, Pinheiro et al. 2017) in R 3.6.0 (R Core Team 2019).

193

## 194 **Results**

### 195 *Climate variability and $CV_\lambda$*

196 In both active and inactive seasons, species' lifespan was negatively associated with  $CV_\lambda$ , indicating  
197 higher temporal variability in annual population growth rates for short-lived species than for long-lived  
198 species (Tables 1 and 2; Fig. 2a - note that in Fig. 2a, the high values of  $CV_\lambda$  when lifespan = 30 represent  
199 a single population of Eastern box turtles). Longitude was a significant covariate in both models (Table  
200 2). During the active season,  $SD_{Temp}$  correlated positively with  $CV_\lambda$  across taxa (Table 2; Fig. 2b),  
201 suggesting that the annual population growth rate fluctuated slightly more under variable than under  
202 stable climatic conditions. Moreover, the relationship between  $CV_{Prec}$  and  $CV_\lambda$  differed between taxa as  
203 indicated by a significant interaction between  $CV_{Prec}$  and taxonomic group in the active season (Table 2).  
204  $CV_\lambda$  tended to increase with increasing  $CV_{Prec}$  for herbaceous plants, while it decreased for amphibians;  
205 insects and mammals were less responsive to  $CV_{Prec}$  (Fig. 2c). During the inactive season, the relationship  
206 between  $SD_{Temp}$  and  $CV_\lambda$  differed between taxa, with the  $CV_\lambda$  of herbaceous plants showing a positive

207 response (Table 2, Fig. 3). Additionally,  $CV_\lambda$  did increase slightly with increasing mean precipitation in  
208 the inactive season (Table 2).

209

### 210 *Climate variability and $|\log \lambda|$*

211 The absolute value of the long-term population growth rate,  $|\log \lambda|$ , declined with increasing lifespan and  
212 with increasing longitude (Table 3). In the active season, the relationship between  $CV_{Prec}$  and  $|\log \lambda|$   
213 differed between taxa, with particularly insects exhibiting a positive association and mammals a negative  
214 association between these two variables (Table 3, Fig. 4). In the inactive season,  $CV_{Prec}$  was marginally  
215 and positively associated with  $|\log \lambda|$  across taxa (Table 3). Moreover,  $|\log \lambda|$  tended to differ among  
216 taxonomic groups, being lower on average for mammals and herbaceous plants than for insects (Table  
217 3).

218

### 219 **Discussion**

220 For the five taxonomic groups considered (amphibians, insects, mammals, herbaceous plants, reptiles)  
221 from the Northern Hemisphere, we found some support for our first hypothesis that climate variability  
222 translates into temporal variation in the annual population growth rates ( $CV_\lambda$ ). We detected a positive  
223 relationship between  $CV_\lambda$  and  $SD_{Temp}$  across taxa in the active season. Moreover, for herbaceous plants,  
224  $CV_\lambda$  increased with the increasing variability of precipitation and temperature in the active and inactive  
225 seasons, respectively. Our second hypothesis of a positive relationship between climate variability and  
226 the absolute value of the long-term population growth rate ( $|\log \lambda|$ ) particularly for short-lived species  
227 was not supported; we observed no interaction between the climate variability and lifespan regarding  $|\log$   
228  $\lambda|$ . Overall, our results suggest that different taxonomic groups were weakly affected by the observed  
229 climate variability during the study period.

230 *Climate variability and  $CV_\lambda$*

231 In the present study, inferences about the effect of climate variability on population fluctuations partially  
232 depended on the season, with the active and inactive seasons yielding different outcomes. When the  
233 effect of climate variability was assessed based on the active season, variation in temperature was weakly  
234 positively associated with  $CV_\lambda$ . We also found that  $CV_\lambda$  for herbaceous plants slightly increased with  
235 increasing  $CV_{Prec}$  in the active season. These findings were thus in line with our predictions. In the  
236 inactive season, associations between climate variability and population fluctuations were less  
237 prominent; a positive association between  $SD_{Temp}$  and  $CV_\lambda$  was detected only for plants. The discrepancy  
238 between the two seasons might be due to the greater importance of environmental conditions on  
239 populations during the active season. Our results indicate that, particularly for herbaceous plant  
240 populations, increasing climatic variability might increase their vulnerability to other sources of variation  
241 OR// to other biotic and abiotic factors // and to extinction by increasing their fluctuations (however, we  
242 did not detect an effect on their  $|\log \lambda|$ ). Contrary to our expectations, we also found a negative  
243 relationship between  $CV_\lambda$  and  $CV_{Prec}$  for amphibians. This result diverges from that reported previously  
244 in a meta-analysis for amphibians in the Northern hemisphere, in which no significant relationship  
245 between yearly rainfall and the magnitude of population fluctuations was observed (Marsh 2001). These  
246 different findings might be due to heterogeneous responses of individual populations. Climatic  
247 conditions, including rainfall and drought conditions, are known to influence population dynamics in  
248 many amphibian species, but populations responses to these main climate drivers can be highly  
249 heterogeneous in direction and magnitude both among and within taxa (Cayuela et al. 2016, Muths et al.  
250 2017). However, a correlative approach, as used in the present study, may also produce spurious  
251 relationships between explanatory variables and the data, particularly if the model is over-parameterized  
252 (Knape and De Valpine 2011), or if some of the explanatory variables are strongly correlated (Zuur et al.  
253 2010). Although over-parameterization and collinearity were not likely in our case, the observed negative

254 relationship between variation in precipitation and  $CV_\lambda$  for amphibians may still be spurious, and reflect  
255 other, non-measured processes that correlate with these climate variables. Indeed, interannual variation  
256 in population growth rates results from a complex assortment of causal interactions including both the  
257 direct and indirect effects of non-climatic factors, such as habitat (e.g., fragmentation or heterogeneity)  
258 and biotic factors (e.g., interspecific competition), which might correlate with climatic conditions (Adler  
259 et al. 2012, Mantyka-Pringle et al. 2012, Oliver and Morecroft 2014, Papanikolaou et al. 2017). As has  
260 been reported in previous studies (García et al. 2008, Morris et al. 2008), we found that short-lived  
261 species exhibited more variable growth rates than long-lived species. This higher variation in the annual  
262 population growth rates of short-lived species was not, however, due to climatic variability, as we  
263 observed no interactions between variation in temperature or precipitation and lifespan. The greater  
264 degree of population fluctuation found in short-lived species (e.g, insects, small mammals) could be due  
265 to other biotic factors, such as the abundance of predators, which may regulate prey population sizes  
266 more directly than local weather conditions (e.g., Hanski et al. 2001).

267 Overall, the observed associations between climate variability and population variability were  
268 statistically significant but weak, which is not surprising given the diversity of taxa that were included.  
269 Indeed, Knappe & De Valpine (2011) reported that climate effects on animal populations are often difficult  
270 to detect in time-series analyses even for large datasets which contain hundreds of time series. Moreover,  
271 we acknowledge the fact that the present study covers a large spatial scale (the Northern Hemisphere),  
272 which may even overestimate the magnitude of population responses to climate variability compared to  
273 studies conducted in single locations (Elmendorf et al. 2015). However, such a large spatial scale  
274 considered should not affect the direction of population response (Elmendorf et al. 2015). As a  
275 consequence, our findings on the effects of observed climate variability on different taxonomic groups  
276 should be interpreted qualitatively rather than quantitatively.

277 *Climate variability and  $|\log \lambda|$*

278 Theory predicts that climate variability can translate into changes in the long-term population growth  
279 rate (Tuljapurkar 1982), but that the direction of these changes is likely to vary across species, depending  
280 on their life history, ecology, and demographic status (Boyce et al. 2006, Lawson et al. 2015, Vázquez  
281 et al. 2015). For instance, empirical findings have indicated that short-lived species might be more  
282 vulnerable to climate variability than long-lived species (Morris et al. 2008, Dalglish et al. 2010),  
283 whereas a previous theoretical study suggests that short-lived species with high reproductive output  
284 might actually benefit from environmental variation (Koons et al. 2009). As observed in many  
285 ectotherms, populations may also respond in a qualitatively different manner to environmental variability  
286 depending on the mean environmental conditions encountered and the geographical location within the  
287 species' range (Bozinovic et al. 2011, García-Carreras and Reuman 2013, Vasseur et al. 2014, Lawson  
288 et al. 2015). Therefore, we used the absolute value of the long-term population growth rates to assess  
289 population responses (regardless of their direction) to climate variability. We hypothesized that the  
290 relationship between  $|\log \lambda|$  and climate variability would be positive for the species that are most  
291 responsive to climate variability, such as shorter-lived species. Despite the fact that temperature  
292 variability in the active season was positively associated with temporal variation in annual population  
293 growth rates across taxa, this variability did not translate into higher absolute values of the long-term  
294 population growth rate,  $|\log \lambda|$ . In contrast to previous studies that have highlighted the essential role of  
295 lifespan in population responses to environmental variability (Morris et al. 2008, Koons et al. 2009,  
296 Dalglish et al. 2010), we observed no such an effect (i.e. the interaction between climate variability and  
297 lifespan was not significant). In other words, changes in the long-term growth rates of both short-lived  
298 and long-lived species were similarly associated with realised climate variability considered. We only  
299 found a negative relationship between  $|\log \lambda|$  and lifespan, suggesting that the populations of short-lived

300 species generally either declined or increased more rapidly than those of longer-lived species. However,  
301 we observed differences in  $|\log \lambda|$  in relation to  $CV_{\text{Prec}}$  in the active season among some taxonomic  
302 groups. The positive relationship between  $CV_{\text{Prec}}$  and  $|\log \lambda|$  of insects, a taxonomic group involving only  
303 short-lived species, suggests that their abundances changed more rapidly when interannual variability in  
304 precipitation was high. In the context of climate change, this result indicates that insects might be  
305 particularly sensitive to expected changes in climate variability.

306 Previous comparative studies across taxa are based on hypothetical climate variability and vital rate  
307 perturbations (Dalglish et al., 2010; Morris et al., 2008), while our study relies on true climate  
308 variability, which can be smaller than hypothetical variability. Therefore, it is possible that no particular  
309 taxonomic group was heavily affected by the observed climate variability during the past 77 years. This  
310 view is also partially supported by a previous study by Palmer et al. (2017), which reported that the  
311 responses of 238 British Lepidoptera and bird species to climate variability since 1968 were species-  
312 specific. From an evolutionary perspective, adaptation to climate variability via demographic buffering  
313 or bet-hedging strategies (e.g., Morris and Doak 2004, Nevoux et al. 2010, but see Jongejans et al. 2010)  
314 could be partially responsible for the lack of a significant correlation between climate variability and  $|\log$   
315  $\lambda|$ . Nevertheless, as we investigated the relationship between climate variability and population responses  
316 at the four-year time scale only, we cannot rule out the possibility that a different timescale might have  
317 revealed a different environmental signal in  $|\log \lambda|$ . For instance, changes in the intra-annual variation of  
318 climate conditions may also affect population fluctuations and, consequently, population growth rates by  
319 modifying the timing of weather conditions and therefore the seasonal abiotic and biotic environments  
320 of a population (e.g., Shriver 2016, Papanikolaou et al. 2017). Similarly, the resolution of climate data  
321 may also affect the conclusions of climate effects (Morrison et al. 2019). In the present study, the

322 resolution of climate surface was rather coarse, but the same resolution has been used also previously for  
323 multispecies studies (e.g., Knape and De Valpine 2011, Spooner et al. 2018).

324 In summary, the present study suggests that temporal fluctuations in population growth rates and the  
325 magnitude of long-term population growth rates are partially associated with short-term interannual  
326 climate variability, but that these associations may vary depending on the season and taxonomic groups  
327 considered. Species lifespan did not explain sensitivity to observed climate variability in our study. These  
328 findings thus indicate that populations might respond individualistically to climate fluctuations and that  
329 factors other than the observed climate variability (e.g., density dependence, biotic interactions, local  
330 microclimate) are probably more important to the dynamics of wild populations.

331 **References**

- 332 Adler, P. B. et al. 2012. Forecasting plant community impacts of climate variability and change: when  
333 do competitive interactions matter? - *J. Ecol.* 100: 478–487.
- 334 Bates, D. et al. 2015. Fitting Linear Mixed-Effects Models Using lme4. - *J. Stat. Softw.* 67: 1–48.
- 335 Boyce, M. S. et al. 2006. Demography in an increasingly variable world. - *Trends Ecol. Evol.* 21: 141–  
336 148.
- 337 Bozinovic, F. et al. 2011. The mean and variance of environmental temperature interact to determine  
338 physiological tolerance and fitness. - *Physiol. Biochem. Zool.* 84: 543–552.
- 339 Bozinovic, F. et al. 2016. Thermal tolerance and survival responses to scenarios of experimental  
340 climatic change: changing thermal variability reduces the heat and cold tolerance in a fly. - *J.*  
341 *Comp. Physiol. B* 186: 581–587.
- 342 Burnham, K. P. and Anderson, D. R. 2002. Model selection and multi-model inference: a practical  
343 information-theoretic approach. - Springer-Verlag, New York.
- 344 Cayuela, H. et al. 2016. Demographic responses to weather fluctuations are context dependent in a  
345 long-lived amphibian. - *Glob. Chang. Biol.* 22: 2676–2687.
- 346 Colchero, F. et al. 2019. The diversity of population responses to environmental change. - *Ecol. Lett.*  
347 22: 342–353.
- 348 Collen, B. et al. 2009. Monitoring Change in Vertebrate Abundance: the Living Planet Index. -  
349 *Conserv. Biol.* 23: 317–327.
- 350 Dalglish, H. J. et al. 2010. Can life-history traits predict the response of forb populations to changes in  
351 climate variability? - *J. Ecol.* 98: 209–217.

- 352 Deguines, N. et al. 2017. Precipitation alters interactions in a grassland ecological community. - J.  
353 Anim. Ecol. 86: 262–272.
- 354 Doak, D. F. et al. 2005. Correctly estimating how environmental stochasticity influences fitness and  
355 population growth. - Am. Nat. 166: E14–E21.
- 356 Drake, J. M. 2005. Population effects of increased climate variation. - Proc. R. Soc. London B 272:  
357 1823–1827.
- 358 Elmendorf, S. C. et al. 2015. Experiment, monitoring, and gradient methods used to infer climate  
359 change effects on plant communities yield consistent patterns. - Proc. Natl. Acad. Sci. 112: 448–  
360 452.
- 361 García-Carreras, B. and Reuman, D. C. 2013. Are Changes in the Mean or Variability of Climate  
362 Signals More Important for Long-Term Stochastic Growth Rate? - PLoS One in press.
- 363 García, M. B. et al. 2008. Life span correlates with population dynamics in perennial herbaceous  
364 plants. - Am. J. Bot. 95: 258–262.
- 365 Genovart, M. et al. 2013. Contrasting effects of climatic variability on the demography of a trans-  
366 equatorial migratory seabird. - J. Anim. Ecol. 82: 121–130.
- 367 Hanski, I. et al. 2001. Small-rodent dynamics and predation. - Ecology 82: 1505–1520.
- 368 Harris, I. et al. 2014. Updated high-resolution grids of monthly climatic observations - the CRU TS3.10  
369 Dataset. - Int. J. Climatol. 34: 623–642.
- 370 Huntingford, C. et al. 2013. No increase in global temperature variability despite changing regional  
371 patterns. - Nature 500: 327–330.
- 372 IPCC 2014. Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to

- 373 the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. - [Core Writing  
374 Team, R.K. Pachauri and L.A. Meyer (eds.)].
- 375 Jenouvrier, S. et al. 2015. Extreme climate events and individual heterogeneity shape life- history traits  
376 and population dynamics. - *Ecol. Monogr.* 85: 605–624.
- 377 Jones, K. E. et al. 2009. PanTHERIA: a species-level database of life history, ecology, and geography  
378 of extant and recently extinct mammals. - *Ecology* 90: 2648–2648.
- 379 Jongejans, E. et al. 2010. Plant populations track rather than buffer climate fluctuations. - *Ecol. Lett.*  
380 13: 736–743.
- 381 Jonzén, N. et al. 2010. Stochastic demography and population dynamics in the red kangaroo *Macropus*  
382 *rufus*. - *J. Anim. Ecol.* 79: 109–116.
- 383 Knape, J. and De Valpine, P. 2011. Effects of weather and climate on the dynamics of animal  
384 population time series. - *Proc. R. Soc. B Biol. Sci.* 278: 985–992.
- 385 Koons, D. N. et al. 2009. Is life-history buffering or lability adaptive in stochastic environments? -  
386 *Oikos* 118: 972–980.
- 387 Lawson, C. R. et al. 2015. Environmental variation and population responses to global change. - *Ecol.*  
388 *Lett.* 18: 724–736.
- 389 Lewontin, R. C. and Cohen, D. 1969. On population growth in a randomly varying environment. -  
390 *Proc. Natl. Acad. Sci.* 62: 1056–1060.
- 391 Mantyka-Pringle, C. S. et al. 2012. Interactions between climate and habitat loss effects on  
392 biodiversity: A systematic review and meta-analysis. - *Glob. Chang. Biol.* 18: 1239–1252.
- 393 Marsh, D. M. 2001. Fluctuations in amphibian populations: a meta-analysis. - *Biol. Conserv.* 101: 327–

394 335.

395 Mills, S. C. et al. 2017. European butterfly populations vary in sensitivity to weather across their  
396 geographical ranges. - *Glob. Ecol. Biogeogr.* 26: 1374–1385.

397 Morris, W. F. and Doak, D. F. 2002. *Quantitative conservation biology*. - Sinauer, Sunderland,  
398 Massachusetts, USA.

399 Morris, W. F. and Doak, D. F. 2004. Buffering of life histories against environmental stochasticity:  
400 accounting for a spurious correlation between the variabilities of vital rates and their contributions  
401 to fitness. - *Am. Nat.* 163: 579–590.

402 Morris, W. F. et al. 2008. Longevity can buffer plant and animal populations against changing climate  
403 variability. - *Ecology* 89: 19–25.

404 Morrison, B. D. et al. 2019. Spatial scale affects novel and disappeared climate change projections in  
405 Alaska. - *Ecol. Evol.* 9: 12026–12044.

406 Moss, S. R. et al. 2004. Symposium The Broadbalk long-term experiment at Rothamsted: what has it  
407 told us about weeds? - *Weed Sci.* 52: 864–873.

408 Muths, E. et al. 2017. Heterogeneous responses of temperate-zone amphibian populations to climate  
409 change complicates conservation planning. - *Sci. Rep.* 7: 1–10.

410 Nakagawa, S. and Schielzeth, H. 2013. A general and simple method for obtaining  $R^2$  from generalized  
411 linear mixed-effects models. - *Methods Ecol. Evol.* 4: 133–142.

412 Nakagawa, S. et al. 2017. The coefficient of determination  $R^2$  and intra-class correlation coefficient  
413 from generalized linear mixed-effects models revisited and expanded. - *J. R. Soc. Interface* 14:  
414 20170213.

415 NERC Centre for Population biology, I. C. 2010. The Global Population Dynamics Database v2.0.

416 Nevoux, M. et al. 2010. Bet-hedging response to environmental variability, an intraspecific  
417 comparison. - *Ecology* 91: 2416–2427.

418 Oliver, T. H. and Morecroft, M. D. 2014. Interactions between climate change and land use change on  
419 biodiversity: attribution problems, risks, and opportunities. - *Wiley Interdiscip. Rev. Clim. Chang.*  
420 5: 317–335.

421 Palmer, G. et al. 2017. Climate change, climatic variation and extreme biological responses. - *Philos.*  
422 *Trans. R. Soc. B Biol. Sci.* 372: 20160144.

423 Papanikolaou, A. D. et al. 2017. Landscape heterogeneity enhances stability of wild bee abundance  
424 under highly varying temperature, but not under highly varying precipitation. - *Landsc. Ecol.* 32:  
425 581–593.

426 Parmesan, C. and Yohe, G. 2003. A globally coherent fingerprint of climate change impacts across  
427 natural systems. - *Nature* 421: 37–42.

428 Pendergrass, A. G. et al. 2017. Precipitation variability increases in a warmer climate. - *Sci. Rep.* 7:  
429 17966.

430 Pinheiro, J. C. et al. 2017. nlme: Linear and Nonlinear Mixed Effects Models. R package version 3.1-  
431 131.

432 Post, E. and Stenseth, N. C. 1999. Climatic Variability, Plant Phenology, and Northern Ungulates. -  
433 *Ecology* 80: 1322–1339.

434 R Core Team 2019. R: A language and environment for statistical computing. R Foundation for  
435 Statistical Computing, Vienna, Austria.

- 436 Roland, J. and Matter, S. F. 2013. Variability in winter climate and winter extremes reduces population  
437 growth of an alpine butterfly. - *Ecology* 94: 190–199.
- 438 Shriver, R. K. 2016. Quantifying how short-term environmental variation leads to long-term  
439 demographic responses to climate change. - *J. Ecol.* 104: 65–78.
- 440 Sokal, R. R. and Rohlf, J. F. 1995. *Biometry: the Principles and Practice of Statistics in Biological*  
441 *Research* (WH Freeman and Company, Ed.).
- 442 Spooner, F. E. B. et al. 2018. Rapid warming is associated with population decline among terrestrial  
443 birds and mammals globally. - *Glob. Chang. Biol.* 24: 4521–4531.
- 444 Teller, B. J. et al. 2016. Linking demography with drivers: climate and competition. - *Methods Ecol.*  
445 *Evol.* 7: 171–183.
- 446 Tuljapurkar, S. D. 1982. Population dynamics in variable environments. II. Correlated environments,  
447 sensitivity analysis and dynamics. - *Theor. Popul. Biol.* 21: 114–140.
- 448 van de Pol, M. et al. 2010. Effects of climate change and variability on population dynamics in a long-  
449 lived shorebird. - *Ecology* 91: 1192–1204.
- 450 van de Pol, M. et al. 2017. Behavioural, ecological and evolutionary response to extreme climatic  
451 events: Challenges & directions. - *Philos. Trans. R. Soc. B Biol. Sci.*: this volume.
- 452 Vasseur, D. A. et al. 2014. Increased temperature variation poses a greater risk to species than climate  
453 warming. - *Proc. R. Soc. B Biol. Sci.* 281: 20132612.
- 454 Vázquez, D. P. et al. 2015. Ecological and evolutionary impacts of changing climatic variability. - *Biol.*  
455 *Rev.* 92: 22–42.
- 456 Walther, G.-R. et al. 2002. Ecological responses to recent climate change. - *Nature* 416: 389–395.

- 457 Williams, C. M. et al. 2015. Cold truths: How winter drives responses of terrestrial organisms to  
458 climate change. - *Biol. Rev.* 90: 214–235.
- 459 Zuur, A. F. et al. 2009. Mixed effects models and extensions in ecology with R (M Gail, K Krickeberg,  
460 JM Samet, A Tsiatis, and W Wong, Eds.). - Springer, New York.
- 461 Zuur, A. F. et al. 2010. A protocol for data exploration to avoid common statistical problems. -  
462 *Methods Ecol. Evol.* 1: 3–14.
- 463 **Data Accessibility:** Data supporting the results are available in the GPDD and LPI databases and  
464 published sources (detailed in Table S1.1, Appendix S1).

465 **Table 1.** Model selection table for the temporal variability in the annual population growth rates ( $CV_\lambda$ )  
466 and the absolute value of the long-term population growth rate ( $|\log \lambda|$ ) calculated across a four-year  
467 sliding time window. Linear mixed-effects models were fitted using a first-order autoregressive structure  
468 and Population ID was treated as a random effect. Climatic mean and variability variables in the active  
469 and inactive season were investigated separately. The best models ( $\Delta AICc < 2$ , in italics) and the full  
470 model ( $M_{Full}$ ) are presented with corresponding df (number of parameters), AICc (Akaike's Information  
471 Criterion), and  $\Delta AICc$ . See Appendix S2, Tables S2.2-S2.5 for the full model selection.

NAM E	DF	AICc	$\Delta AICc$	MODEL DESCRIPTION
<i>CV<sub>λ</sub> - active season</i>				
<i>M1</i>	17	-187.34	0.00	<i>CV<sub>Prec</sub> + SD<sub>Temp</sub> + group + lifespan + longitude + latitude + CV<sub>Prec:group</sub></i>
<i>M2</i>	16	-187.04	0.29	<i>CV<sub>Prec</sub> + SD<sub>Temp</sub> + group + lifespan + longitude + CV<sub>Prec:group</sub></i>
<i>M3</i>	18	-185.35	1.99	<i>CV<sub>Prec</sub> + SD<sub>Temp</sub> + group + lifespan + longitude + latitude + mean<sub>Prec</sub> + CV<sub>Prec:group</sub></i>
<b>M<sub>Full</sub></b>	25	-179.53	7.81	<b>CV<sub>Prec</sub> + SD<sub>Temp</sub> + group + lifespan + longitude + latitude + mean<sub>Temp</sub> + mean<sub>Prec</sub> + CV<sub>Prec:group</sub> + SD<sub>Temp:group</sub> + CV<sub>Prec:lifespan</sub> + SD<sub>Temp:lifespan</sub></b>
<i>CV<sub>λ</sub> - inactive season</i>				
<i>M1</i>	17	-183.24	0.00	<i>SD<sub>Temp</sub> + group + lifespan + longitude + latitude + mean<sub>Prec</sub> + SD<sub>Temp:group</sub></i>
<i>M2</i>	16	-182.89	0.35	<i>SD<sub>Temp</sub> + group + lifespan + longitude + mean<sub>Prec</sub> + SD<sub>Temp:group</sub></i>
<i>M3</i>	18	-181.39	1.84	<i>SD<sub>Temp</sub> + group + lifespan + longitude + latitude + mean<sub>Prec</sub> + CV<sub>Prec</sub> + SD<sub>Temp:group</sub></i>
<b>M<sub>Full</sub></b>	25	-168.44	14.79	<b>CV<sub>Prec</sub> + SD<sub>Temp</sub> + group + lifespan + longitude + latitude + mean<sub>Temp</sub> + mean<sub>Prec</sub> + CV<sub>Prec:group</sub> + SD<sub>Temp:group</sub> + CV<sub>Prec:lifespan</sub> + SD<sub>Temp:lifespan</sub></b>
<i> \log λ  - active season</i>				
<i>M1</i>	17	-272.12	0	<i>CV<sub>Prec</sub> + SD<sub>Temp</sub> + group + lifespan + longitude + mean<sub>Temp</sub> + CV<sub>Prec:group</sub></i>
<i>M2</i>	18	-270.54	1.58	<i>CV<sub>Prec</sub> + SD<sub>Temp</sub> + group + lifespan + longitude + mean<sub>Temp</sub> + mean<sub>Prec</sub> + CV<sub>Prec:group</sub></i>
<i>M3</i>	16	-270.42	1.70	<i>CV<sub>Prec</sub> + SD<sub>Temp</sub> + group + lifespan + longitude + CV<sub>Prec:group</sub></i>
<i>M4</i>	16	-270.40	1.72	<i>CV<sub>Prec</sub> + group + lifespan + longitude + mean<sub>Temp</sub> + CV<sub>Prec:group</sub></i>
<i>M5</i>	18	-270.14	1.98	<i>CV<sub>Prec</sub> + SD<sub>Temp</sub> + group + lifespan + longitude + latitude + mean<sub>Temp</sub> + CV<sub>Prec:group</sub></i>
<b>M<sub>Full</sub></b>	25	-263.72	8.40	<b>CV<sub>Prec</sub> + SD<sub>Temp</sub> + group + lifespan + longitude + latitude + mean<sub>Temp</sub> + mean<sub>Prec</sub> + CV<sub>Prec:group</sub> + SD<sub>Temp:group</sub> + CV<sub>Prec:lifespan</sub> + SD<sub>Temp:lifespan</sub></b>
<i> \log λ  - inactive season</i>				
<i>M1</i>	11	-267.49	0	<i>CV<sub>Prec</sub> + group + lifespan + longitude</i>
<b>M<sub>Full</sub></b>	25	-255.30	12.19	<b>CV<sub>Prec</sub> + SD<sub>Temp</sub> + group + lifespan + longitude + latitude + mean<sub>Temp</sub> + mean<sub>Prec</sub> + CV<sub>Prec:group</sub> + SD<sub>Temp:group</sub> + CV<sub>Prec:lifespan</sub> + SD<sub>Temp:lifespan</sub></b>

472 Abbreviations: CV<sub>Prec</sub>= precipitation coefficient of variation during a given season (scaled per population); SD<sub>Temp</sub>= temperature  
473 standard deviation during a given season (scaled per population); mean<sub>Prec</sub>= mean precipitation during a given season (scaled

474 per population);  $mean_{Temp}$ = mean temperature during a given season (scaled per population); group= taxonomic groups  
 475 (amphibians, insects, mammals, herbaceous plants and reptiles).

476 **Table 2.** Results from the simplified mixed models that best explained the interannual variability in  
 477 population growth rates ( $CV_{\lambda}$ ) across taxa (n=59 populations from the Northern Hemisphere; Models  
 478 M2 for the active and inactive seasons in Table 1). All continuous variables were scaled based on  
 479 detrended data. The estimates, the 95% confidence intervals (95% CI) and marginal  $R^2$  values  
 480 (conditional  $R^2$  in brackets) are presented.

	Estimate	95% CI	Intercept	Residual	$R^2$
<b>Active season</b>					
<b>Fixed factors</b>					
<i>Intercept</i>	0.55	[0.38, 0.72]			
<i>Group</i> <sub>[Insecta]</sub>	0.04	[-0.20, 0.27]			
<i>Group</i> <sub>[Mammalia]</sub>	-0.03	[-0.22, 0.16]			
<i>Group</i> <sub>[Herb. plant]</sub>	-0.01	[-0.21, 0.18]			
<i>Group</i> <sub>[Reptilia]</sub>	0.13	[-0.10, 0.36]			
<i>Lifespan</i>	-0.12	[-0.18, 0.06]			
<i>Longitude</i>	-0.09	[-0.15, 0.04]			
<i>SD<sub>Temp</sub></i>	0.02	[0.01, 0.04]			
<i>CV<sub>Prec</sub></i>	-0.06	[-0.12, 0.01]			
<i>CV<sub>Prec</sub>: Group</i> <sub>[Insecta]</sub>	0.06	[-0.02, 0.14]			
<i>CV<sub>Prec</sub>: Group</i> <sub>[Mammalia]</sub>	0.05	[-0.01, 0.12]			
<i>CV<sub>Prec</sub>: Group</i> <sub>[Herb. plant]</sub>	0.09	[0.02, 0.16]			
<i>CV<sub>Prec</sub>: Group</i> <sub>[Reptilia]</sub>	0.08	[0.003, 0.15]			
<b>Random factors</b>					
<i>pop.ID</i>			0.15	0.25	0.15 (0.37)
<b>Inactive season</b>					
<b>Fixed factors</b>					
<i>Intercept</i>	0.55	[0.38, 0.72]			
<i>Group</i> <sub>[Insecta]</sub>	0.04	[-0.20, 0.28]			
<i>Group</i> <sub>[Mammalia]</sub>	-0.03	[-0.22, 0.16]			

<i>Group</i> <sub>[Herb. plant]</sub>	-0.01	[-0.21, 0.18]			
<i>Group</i> <sub>[Reptilia]</sub>	0.13	[-0.10, 0.36]			
<i>Lifespan</i>	-0.12	[-0.18, -0.06]			
<i>Longitude</i>	-0.09	[-0.15, -0.04]			
<i>Mean</i> <sub>Prec</sub>	0.02	[0.01, 0.04]			
<i>SD</i> <sub>Temp</sub>	-0.03	[-0.08, 0.02]			
<i>SD</i> <sub>Temp</sub> : <i>Group</i> <sub>[Insecta]</sub>	0.01	[-0.05, 0.07]			
<i>SD</i> <sub>Temp</sub> : <i>Group</i> <sub>[Mammalia]</sub>	0.04	[-0.02, 0.09]			
<i>SD</i> <sub>Temp</sub> : <i>Group</i> <sub>[Herb. plant]</sub>	0.07	[0.01, 0.12]			
<i>SD</i> <sub>Temp</sub> : <i>Group</i> <sub>[Reptilia]</sub>	0.02	[-0.04, 0.08]			
<b>Random factors</b>					
<i>pop.ID</i>			0.15	0.25	0.15 (0.36)

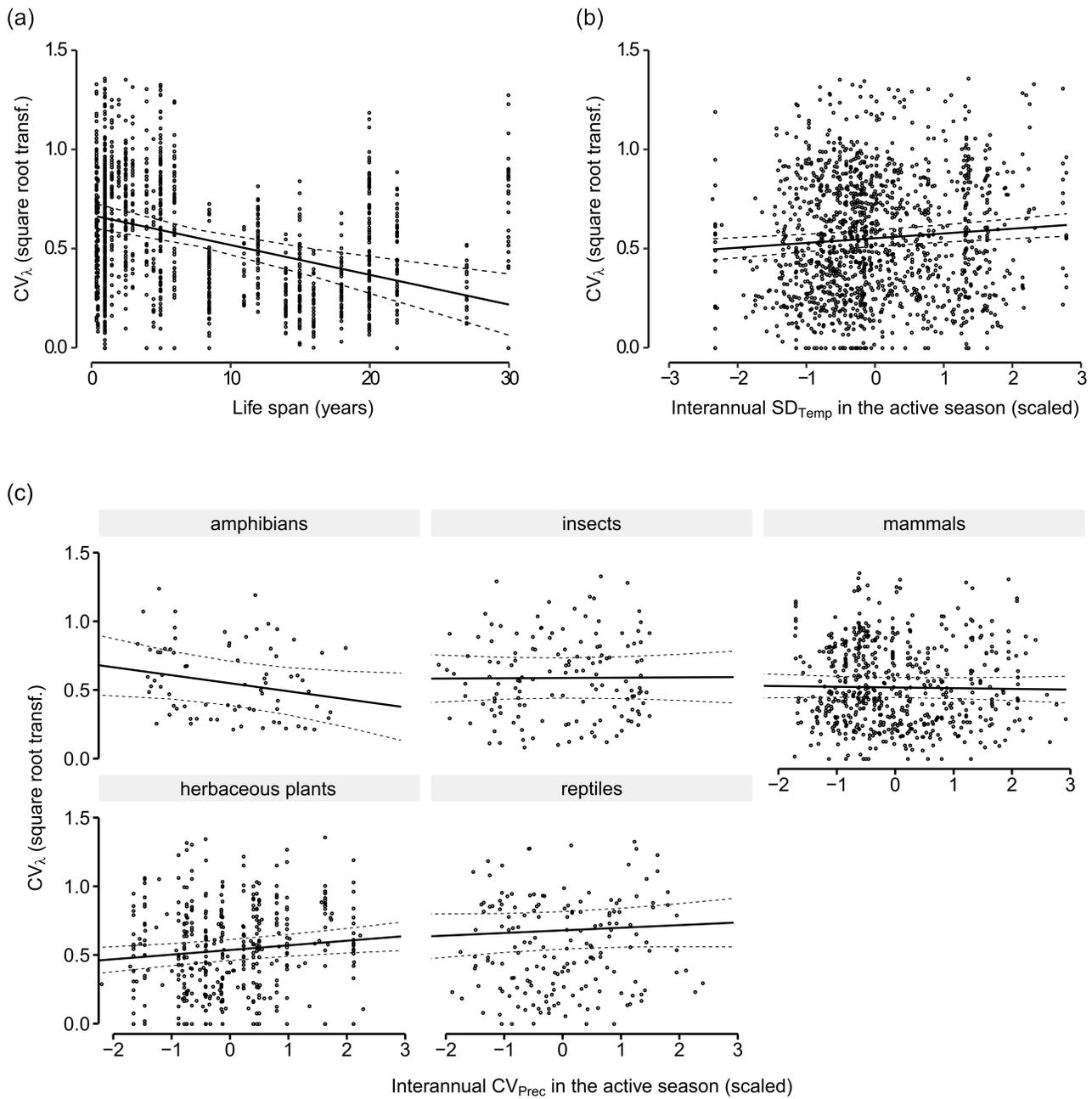
482 **Table 3.** Results from the simplified mixed models that best explained the variability in the absolute  
 483 value of the long-term population growth rate ( $|\log \lambda|$ ) across taxa (n=59 populations from the Northern  
 484 Hemisphere). All continuous variables were scaled. The estimates, the 95% confidence intervals and  
 485 marginal  $R^2$  values (conditional  $R^2$  in brackets) of model M3 for the active season and M1 for the inactive  
 486 season (Table 1) are presented.

	<i>Estimate</i>	<i>95% CI</i>	<i>Intercept</i>	<i>Residual</i>	<i>R<sup>2</sup></i>
<b>Active season</b>					
<b>Fixed factors</b>					
<i>Intercept</i>	0.43	[0.32, 0.55]			
<i>Group</i> <sub>[Insecta]</sub>	0.11	[-0.06, 0.27]			
<i>Group</i> <sub>[Mammalia]</sub>	-0.09	[-0.22, 0.04]			
<i>Group</i> <sub>[Herb. plant]</sub>	-0.06	[-0.20, 0.07]			
<i>Group</i> <sub>[Reptilia]</sub>	0.01	[-0.15, 0.17]			
<i>Lifespan</i>	-0.07	[-0.1, -0.03]			
<i>Longitude</i>	-0.06	[-0.10, -0.02]			
<i>CV<sub>Prec</sub></i>	-0.01	[-0.06, 0.04]			
<i>SD<sub>Temp</sub></i>	0.01	[-0.001, 0.02]			
<i>CV<sub>Prec</sub>: Group</i> <sub>[Insecta]</sub>	0.05	[-0.02, 0.11]			
<i>CV<sub>Prec</sub>: Group</i> <sub>[Mammalia]</sub>	-0.02	[-0.08, 0.04]			
<i>CV<sub>Prec</sub>: Group</i> <sub>[Herb. plant]</sub>	0.03	[-0.03, 0.09]			
<i>CV<sub>Prec</sub>: Group</i> <sub>[Reptilia]</sub>	0.02	[-0.04, 0.08]			
<b>Random factors</b>					
<i>Pop.ID</i>			0.11	0.21	0.13 (0.30)
<b>Inactive season</b>					
<b>Fixed factors</b>					
<i>Intercept</i>	0.43	[0.32, 0.55]			
<i>Group</i> <sub>[Insecta]</sub>	0.11	[-0.06, 0.27]			
<i>Group</i> <sub>[Mammalia]</sub>	-0.09	[-0.22, 0.04]			
<i>Group</i> <sub>[Herb. plant]</sub>	-0.06	[-0.20, 0.07]			
<i>Group</i> <sub>[Reptilia]</sub>	0.01	[-0.15, 0.17]			
<i>Lifespan</i>	-0.07	[-0.11, -0.03]			
<i>Longitude</i>	-0.06	[-0.10, -0.02]			
<i>CV<sub>Prec</sub></i>	0.01	[0.002, 0.03]			
<b>Random factors</b>					
<i>Pop.ID</i>			0.11	0.21	0.12 (0.29)

487

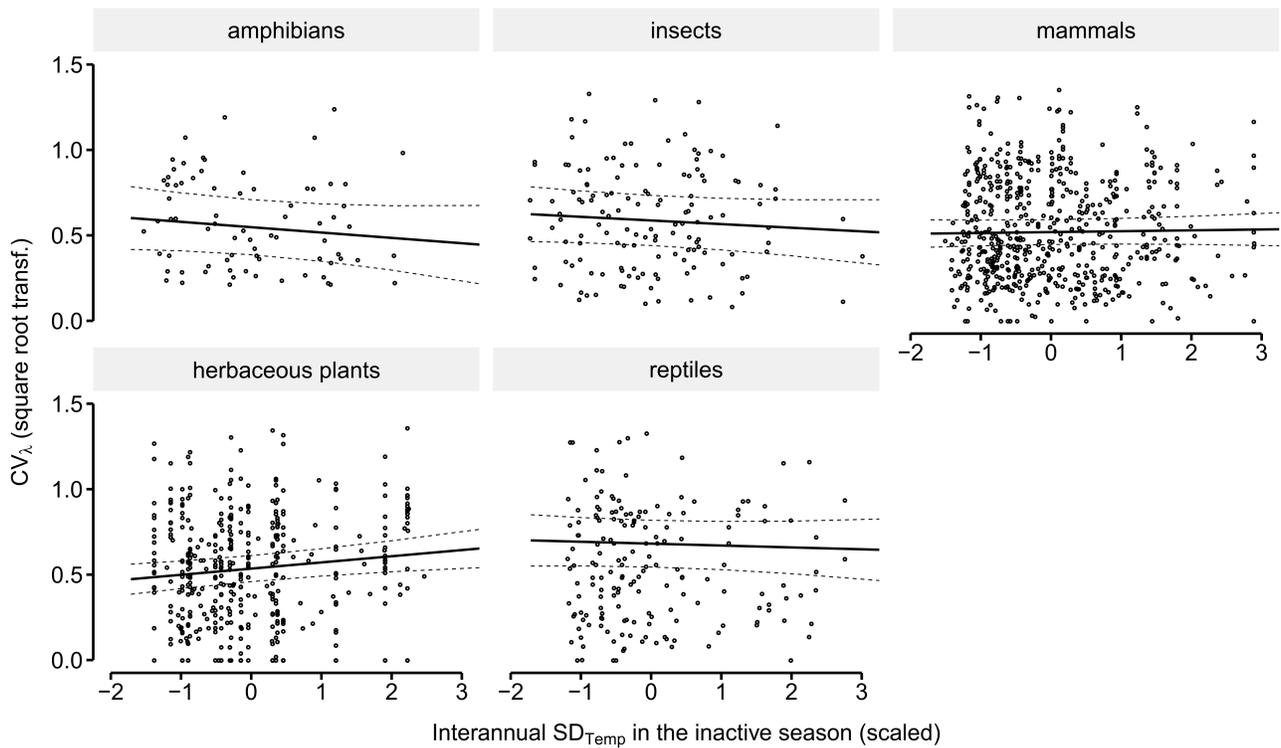


491 **Figure 2.** Temporal variability in annual population growth rates ( $CV_\lambda$ ) calculated across a four-year  
 492 sliding time window for 59 populations from the Northern Hemisphere and plotted against (a) species'  
 493 lifespan, (b) variation in temperature ( $SD_{Temp}$ ) across taxa in the active season, and (c) variation in  
 494 precipitation in the active season ( $CV_{Prec}$ ) for each taxonomic group. The fitted lines with 95% confidence  
 495 intervals are estimated from model M2, Table 1 ( $CV_\lambda$  - active season).



496

497 **Figure 3.** Temporal variability in annual population growth rates ( $CV_\lambda$ ) calculated across a four-year  
498 sliding time window for 59 populations from the Northern Hemisphere and plotted against variation in  
499 temperature ( $SD_{Temp}$ ) in the inactive season for each taxonomic group considered. The fitted lines with  
500 95% confidence intervals are from the mixed model M2, Table 1 ( $CV_\lambda$  - inactive season).



501

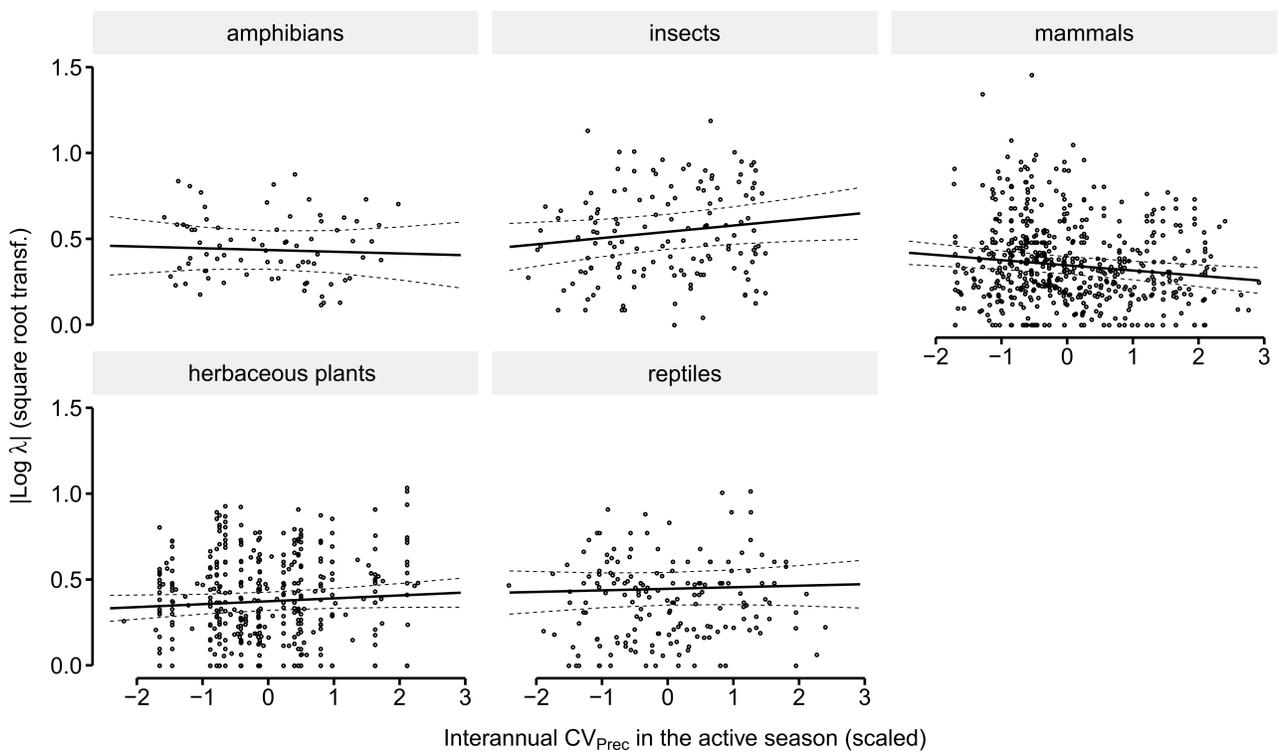
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506 **Figure 4.** Relationships between the absolute value of the long-term population growth rate ( $|\log \lambda|$ ) and  
507 the variation in precipitation ( $CV_{Prec}$ ) in the active season, for each taxonomic group considered (based  
508 on 59 populations from the Northern Hemisphere). Values are calculated across a four-year sliding time  
509 window, the fitted values (black) with 95% confidence intervals are from the linear mixed model M3,  
510 Table 1 ( $|\log \lambda|$  - active season).



511