

1 **Title:** Climate, latitude, and land cover predict flying insect biomass across a German malaise  
2 trap network

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60 **ABSTRACT**

61 Using data from the first year of a new, long-term, standardized German Malaise Trap Program  
62 coordinated by the German Long-Term Ecological Research network, we apply an ecological  
63 gradients approach to examine the effects of climate and land cover on flying insect biomass. We  
64 hypothesized that biomass would display a unimodal relationship with temperature, consistent  
65 with thermal performance theory, would decrease with precipitation due to reduced flying  
66 activity, and would decrease in areas with more heavily human-modified land cover. Flying  
67 insect biomass was quantified from malaise traps at 84 locations across Germany throughout the  
68 2019 growing season. We used an AIC<sub>c</sub> approach to parse drivers of temperature, deviation in  
69 2019 temperature from long-term averages, precipitation, land cover, geographic coordinates,  
70 elevation, and sampling period. We further examined how effects of temperature on insect  
71 biomass change across space by testing for interactions between temperature and latitude. Flying  
72 insect biomass increased linearly with monthly temperature across all samples. However,  
73 positive effects of temperature on flying insect biomass declined with latitude, suggesting the  
74 warm 2019 summer temperatures in southern Germany may have exceeded local insect  
75 optimums, and highlighting the spatial variation in climate change-driven impacts on insect  
76 communities. Land cover explained less variation in insect biomass, with the largest effect being  
77 lower biomass in forested sites. Future work from this newly begun German Malaise Trap  
78 Program will add a multi-year dimension to this large-scale, distributed sampling network, with  
79 the aim of disentangling the roles of multiple drivers on flying insect communities.

80

81 **Keywords:** ecological gradient, climate change, insect monitoring, observational, distributed,  
82 malaise, pollinator, land use, thermal performance, LTER

## 83 INTRODUCTION

84 Amidst growing evidence of widespread insect declines, there has been an increasing call for  
85 high quality, standardized, and large scale insect monitoring to improve estimates of trends, and  
86 identify drivers (Didham *et al.*, 2020; Wagner, 2020). Insects, and flying insects in particular, are  
87 hyper-diverse and provide critical ecological services, including pollination of both wild species  
88 and 75% of crop plants, decomposition, and pest control (Losey & Vaughan, 2006; Klein *et al.*,  
89 2007; Vanbergen & Insect Pollinators Initiative, 2013; Reilly *et al.*, 2020). Additionally, insect  
90 biomass is a key component of energy flows for many food webs (Stepanian *et al.*, 2020).  
91 Biomass is a useful indicator of ecosystem function (Dangles *et al.*, 2011; Barnes *et al.*, 2016),  
92 and is representative of whole insect communities (Shortall *et al.*, 2009; Hallmann *et al.*, 2017).  
93 Climate change and anthropogenically-altered land cover are among the most commonly cited  
94 drivers of insect declines (Habel *et al.*, 2019), but we have yet to understand their full impacts on  
95 insect biomass.

96         The effects of climate change are geographically pervasive (Wilson & Fox, 2020) and  
97 may explain recent reports of insect decline in natural areas (Janzen & Hallwachs, 2019; Rada *et*  
98 *al.*, 2019; Baranov *et al.*, 2020; Welts *et al.*, 2020b). Some insect taxa are currently benefiting  
99 from rising temperatures, which can increase local populations (Kaspari *et al.*, 2019; Baker *et al.*,  
100 2021), diversity (Hofmann *et al.*, 2018), and species' range sizes (Termaat *et al.*, 2019).  
101 However, as temperatures continue to rise and increase more rapidly, temperature is expected to  
102 negatively affect insect productivity (Warren *et al.*, 2018). Thermal performance theory captures  
103 this non-linearity in predicting a unimodal relationship between temperature and insect fitness, as  
104 measured by biomass or other performance indicators (Kingsolver & Huey, 2008; Kühsel &  
105 Blüthgen, 2015; Sinclair *et al.*, 2016; Kaspari *et al.*, 2019).

106           Precipitation may directly and indirectly affect flying insect biomass. High precipitation  
107 may directly cause insect mortality, reducing population sizes, but may also decrease the period  
108 of time insects are flying, reducing trap catch while not reflecting true community biomass  
109 (Totland, 1994). Indirect effects of precipitation on flying insects mediated by plants (e.g.  
110 altering plant phenology or plant nutrition) are context-dependent but increasing rainfall in  
111 average to wet climates is often detrimental (Lawson & Rands, 2019). The predicted response of  
112 precipitation regimes to climate change varies with region, with forecasts for Germany  
113 suggesting slight increases in cumulative annual precipitation but shifts in the timing of rainfall  
114 with longer dry periods, especially in summer (Bender *et al.*, 2017).

115           Changing land cover due to human activities has been described as the largest threat to  
116 insect biodiversity (Wagner, 2020), with wide-ranging impacts from loss of resources and  
117 nesting locations at local scales, to fragmented habitats at larger scales (Newbold *et al.*, 2020).  
118 Heavily human modified landscapes also come with associated pressures, such as eutrophication  
119 and pesticide use with agricultural intensification (Goulson *et al.*, 2018; Carvalheiro *et al.*, 2020),  
120 and light pollution from urban environments (Owens *et al.*, 2020). Urban land cover can result in  
121 declines of both insect diversity (Fenoglio *et al.*, 2020; Piano *et al.*, 2020), and biomass  
122 (Macgregor *et al.*, 2019; Svenningsen *et al.*, 2020).

123           In early 2019, a collaboration between the German Long-Term Ecological Research  
124 network (LTER-D; e.g. Haase *et al.*, 2016) and the German National Natural Landscapes  
125 (Nationale Naturlandschaften; biosphere reserves and national parks) established the German  
126 Malaise Trap Program, a new long-term, standardized, flying insect monitoring initiative of  
127 malaise traps distributed across Germany (<https://www.ufz.de/lter-d/index.php?de=46285>).  
128 Following the first year of monitoring (2019), we examine the effects of climate and surrounding

129 land cover on flying insect biomass across both the growing season (April-October) and a  
130 regional geographic gradient (ranging over 7° latitude, from the German Alps to the Baltic and  
131 North Sea). A recent study (Hallmann *et al.*, 2017) reported flying insect biomass from 63  
132 locations in Germany over 27 years. However, 58 locations were from central-west Germany and  
133 5 were from central-east Germany; thus the sites do not have representative coverage of  
134 Germany or represent an extensive latitudinal gradient (coverage of 2° latitude). Additionally,  
135 the individual year with the most sampling in Hallmann *et al.* (2017) comprised 23 locations.  
136 While our sampling does not yet have the multi-year coverage of Hallmann *et al.* (2017), the  
137 higher number of within year trap locations and broader spatial coverage allows us to examine  
138 drivers of flying insect biomass using a macroecological gradients approach (Pianka, 1966;  
139 Halbritter *et al.*, 2013; Welts & Joern, 2015; Peters *et al.*, 2019).

140 Here we introduce the German Malaise Trap Program and provide a first examination  
141 from this network of the drivers of variation in flying insect biomass. We hypothesize **(1)** that the  
142 effect of temperature on insect biomass will become less positive with increasing temperatures,  
143 consistent with thermal performance theory. Spatially, we predict **(2)** greater increases in flying  
144 insect biomass with increasing temperature in colder sites and weaker to negative effects of  
145 temperature on flying insect biomass at warmer sites. As elevation tends to increase from  
146 northern to southern Germany and may affect temperature, we additionally test for the effects of  
147 elevation on flying insect biomass. We hypothesize **(3)** that flying insect biomass will decline  
148 with increasing precipitation due to reduced flying activity. Finally, we predict **(4)** lower insect  
149 biomass in areas surrounded by more heavily human-modified land cover types such as urban  
150 and agricultural areas (Ricketts *et al.*, 2008; Leather, 2018).

151

## 152 MATERIALS AND METHODS

### 153 *The German Malaise Trap Program*

154 The German Malaise Trap Program currently comprises 31 LTER-D and National Natural  
155 Landscape sites (biosphere reserves and national parks) (Fig. 1). The program was established in  
156 early 2019 with the aim of investigating long-term trends in flying insect biomass and species  
157 composition using DNA metabarcoding. In each site, one to six locations were selected and one  
158 malaise trap was installed per location. For this study, we used the 2019 biomass data retrieved  
159 from 25 of the 31 sites; the remaining six sites began sampling in 2020. To fill in spatial gaps,  
160 we added data from another project comprising 8 sites in Bavaria using the same malaise trap  
161 type and measurement methods. Overall, 1039 samples from 84 malaise trap locations and 33  
162 participating sites widely distributed across Germany (Fig. 1) were included in this study. All  
163 traps were identically constructed with an opening area of 1.16 m<sup>2</sup> on each of the two trap sides  
164 (Fig. S1). Traps predominantly ran from early April to late October 2019. Traps were usually  
165 emptied every two weeks (14.03 days  $\pm$  0.06 SE; range 7 - 29 days). Several samples were lost  
166 due to animal or wind damage. As trap runs varied in length, we use biomass/day as the response  
167 variable for all analyses. By sampling across all times of day for the duration of the growing  
168 season, these data provide representative measures of each location's flying insect community.

169

### 170 *Lab procedures*

171 Insect biomass was weighed while wet to preserve samples for future identification. Following  
172 the procedure in Hallmann et al. (2017), samples were placed in a stainless steel sieve (0.8 mm  
173 mesh width) to remove excess alcohol. Instead of waiting until filtered alcohol drops

174 occurred >10 seconds apart, each sample was filtered for a standard five minutes. Subsequently,  
175 insects were weighted to the nearest 0.01g.

176

### 177 *Climate*

178 Monthly means of maximum and minimum temperatures, and monthly cumulative precipitation  
179 from 2019 were extracted from each sampling location using the Terraclimate dataset  
180 (Abatzoglou *et al.*, 2018). To compare 2019 with long-term climate averages, we extracted  
181 monthly means of maximum and minimum temperature, and monthly cumulative precipitation  
182 from 1960-2018 from each trap location using the CRU-TS 4.03 dataset (Harris *et al.*, 2014)  
183 downscaled with WorldClim 2.1 (Fick & Hijmans, 2017). Two datasets were used because the  
184 data from both time periods (2019 and 1960-2018) were not available from either dataset alone.  
185 Both the Terraclimate and CRU-TS 4.03/ WorldClim 2.1 datasets have spatial resolutions of 2.5  
186 arc minutes ( $\sim 21 \text{ km}^2$ ) with our 84 trap locations occurring in 72 separate climate grid cells.

187       Maximum and minimum temperatures in 2019 were generally higher than 1960-2018  
188 averages, especially during the hottest months (Appendix 1: Fig. S2). While one study suggested  
189 that minimum nightly temperatures are warming at a faster rate than maximum temperatures  
190 which may limit the ability of insects to recover from hot daytime periods (Speights *et al.*, 2017),  
191 we found 2019 maximum monthly temperatures across our trap locations were on average  
192 slightly higher than 1960-2018 averages ( $2.062^\circ\text{C} \pm 0.047 \text{ SE}$ ), than were minimum monthly  
193 temperatures ( $1.938^\circ\text{C} \pm 0.048 \text{ SE}$ ). As mean maximum and minimum monthly temperatures  
194 were highly correlated ( $F_{(1,512)}=4442$ ,  $R^2=0.9$ ,  $P<0.001$ ), we used only mean maximum  
195 temperatures in our analyses. Cumulative annual precipitation was lower in 2019 ( $784 \text{ mm} \pm 32$



196 SE) compared to the long-term 1960-2018 average (842 mm  $\pm$  32 SE). There was no consistent  
197 difference between monthly cumulative precipitation in 2019 and the long-term average, but the  
198 mid-summer months tended to be drier in 2019 (Fig. S2). Both 2019 mean monthly maximum  
199 temperatures and precipitation across our trap locations tended to decline with increasing latitude  
200 (Appendix 1: Fig. S3).

201

## 202 ***Land cover and elevation***

203 Land-cover categories in a 1-km buffer around each sampling location were extracted using the  
204 CORINE Land cover data from 2018 (European Union, Copernicus Land Monitoring Service,  
205 2018). A buffer of 1 km was selected based on previous studies of insect communities that found  
206 land cover effects declined at larger scales (Seibold *et al.*, 2019). Extracted land cover data was  
207 comprised of 30 CORINE land cover categories, which we pooled into eight categories: urban  
208 (7.5% of surrounding land cover), intensive agriculture (2.3%), non-irrigated agriculture  
209 (15.9%), pasture/orchard (12.7%), forest (44.7%), grassland/shrubland (12.1%), freshwater  
210 (3.9%), and saltwater (0.9%). For data visualization purposes, trap locations were additionally  
211 categorized by the dominant land cover within the 1-km buffer: urban (n=6), non-irrigated  
212 agriculture (16), pasture/orchard (6), forest (44), grassland/shrubland (9), freshwater (2), and  
213 saltwater (1).

214 Elevation (m above sea level) was extracted using the Digital Terrain Model with 200-m  
215 grid widths (DGM200) from the German Federal Agency for Cartography and Geodesy  
216 (GeoBasis-DE / BKG, 2013). Locations varied from elevations of 0 m on a barrier island in

217 northeast Germany, to 1413 m in the German Alps. Elevation across our 84 sampling locations  
218 was negatively correlated with latitude (Appendix 1: Fig. S4).

219 All GIS data extraction was conducted in QGIS ver. 3.14 (QGIS.org, 2020).

220

### 221 *AIC<sub>c</sub> analysis*

222 To identify drivers of insect biomass, we used an Akaike Information Criterion corrected for  
223 small sample sizes (AIC<sub>c</sub>) modelling framework (Burnham & Anderson, 2003); first building an  
224 *a priori* full model, and then comparing all possible reduced models using the *dredge* function in  
225 the R package MuMIn (Bartoń, 2016). Mixed models were fit using the R package lme4 (Bates  
226 *et al.*, 2015). All analyses were conducted in R ver. 4.0.3 (R Core Team, 2020). To reduce  
227 variance inflation due to land cover categories being percentages, we sequentially removed land  
228 cover categories from the model starting with the least common until the variance inflation factor  
229 was <10; this removed the land cover types freshwater, intensive agriculture, and saltwater.  
230 Initial analyses substituting the Land Use Index (LUI; Büttner, 2014) for land cover percent  
231 values resulted in no top models containing LUI; thus we opted to use individual land cover  
232 categories. The 2<sup>nd</sup> degree polynomial of the sampling period was included in the model to  
233 capture the hump-shaped pattern of flying insect biomass across the growing season. Sampling  
234 period refers to the half-month period most overlapping the days of sampling, and is numerical  
235 (e.g. first half of April = sampling period 1, second half of April = sampling period 2). Monthly  
236 temperature and precipitation predictors corresponded to the month in which the majority of  
237 sampling days occurred. Monthly temperature was included as a 2<sup>nd</sup> degree polynomial to test  
238 our prediction of a unimodal relationship. One approach to examine our hypothesis that

239 temperature effects varied spatially would be to include the interaction between temperature  
240 variables and latitude; however, this interaction caused variance inflation and thus was not  
241 included. Precipitation and elevation were scaled by dividing by 100. We did not include 2019  
242 precipitation minus the long-term average in our model, as we did for temperature, because it  
243 caused inflated variance and 2019 precipitation was not consistently different from the long-term  
244 average (Fig. S2).

245 The full model contained the response variable of  $\log_{10}(x+1)$  transformed mg/day  
246 biomass, the fixed predictors of the 2nd degree polynomial of 2019 average monthly maximum  
247 temperature ( $\text{poly}(\text{tmax},2)$ ), the difference between 2019 average monthly maximum  
248 temperature and the long-term average temperature ( $\Delta\text{temp}$ ), monthly cumulative precipitation  
249 ( $\text{precip}$ ), latitude, longitude, elevation, % cover of the five most dominant land cover categories  
250 within a 1-km radius around the trap location, a 2<sup>nd</sup> degree polynomial of sampling period to  
251 account for seasonality ( $\text{poly}(\text{period},2)$ ), and a random effect of trap identity (trap) to account for  
252 repeated observations. The form of the mixed model was:

253  $\log_{10}(\text{mg}/\text{day}+1) \sim \text{poly}(\text{tmax},2) + \Delta\text{temp} + \text{precip} + \text{latitude} + \text{longitude} + \text{elevation} + \% \text{forest}$   
254  $+ \% \text{grass/shrubland} + \% \text{pasture/orchard} + \% \text{non-irrigated crop} + \% \text{urban} + \text{poly}(\text{period},2) +$   
255  $(1|\text{trap})$

256

### 257 *Temperature effects across latitudes*

258 While variance inflation prohibited a temperature by latitude interaction term in the mixed  
259 model, we wished to further examine our hypotheses that the effects of temperature on flying  
260 insect biomass would decrease in the warmer lower latitudes. For this analysis, we reduced the

261 dataset to one average biomass value (in mg/day) for each location and month. Calculating  
262 monthly values reduces complexity due to variation in when samples are collected across  
263 locations, and was the first step towards calculating one value of biomass across the growing  
264 season for each sampling location. We estimated the daily biomass collected within each month,  
265 assuming traps caught the same amount of biomass each day within a sample. We pooled  
266 samples within the same month and, for samples spanning more than one month, we allocated  
267 the proportion of biomass from the sample to each month based on the number of sampling days  
268 occurring within the month (e.g. for a trap run with 1 day in month A and 13 days in month B we  
269 assumed 1/14<sup>th</sup> of the biomass was collected in month A and 13/14<sup>th</sup> was in month B). With  
270 these assumptions, the average biomass  $B_{ij}$  (mg/day) of location  $i$  in month  $j$  in location is a  
271 weighted average of the  $n$  samples occurring in the month according to the following formula:

272 **Eq. 1**

$$273 \quad B_{i,j} = \frac{\sum_{k=1}^n (b_{ijk} \times D_{k,j} \div D_k)}{\sum_{k=1}^n D_{k,j}}$$

274 Where  $b_{ijk}$  = the total biomass (mg) at location  $i$  occurring at least partially in month  $j$  for a  
275 sample  $k$ ,  $n$  = the total number of samples occurring at least partially in month  $j$  for location  $i$ ,  $D_{k,j}$   
276 = the number of sampling days occurring in month  $j$  for a given sample  $k$ ,  $D_k$  = the total number  
277 of sampling days for a given sample  $k$

278 To examine how the effect of temperature changed over latitude, we averaged  $B_{i,j}$  across  
279 the seven sampling months (Apr. - Oct.) to calculate one monthly average of mg/day for each  
280 site. We used only the 48 sites which conducted sampling in all seven sampling months. We  
281 calculated average monthly maximum temperature across the same period (Apr. - Oct. 2019),  
282 henceforth “growing season temperature”. Then we examined the linear relationship between

283 monthly averages of mg/day and the interaction between growing season temperature and  
284 latitude. We visualized the interaction between temperature and latitude using the R package  
285 “effects” (Fox & Weisberg, 2019).

286

### 287 *Dominant land cover categories*

288 To further visualize and explore changes in flying insect biomass in the dominant land-cover  
289 categories and across the growing season, we plotted flying insect biomass/day over median  
290 sampling day (numerical day of the year halfway between trap start and end day) for locations  
291 corresponding to each dominant land cover. We used Welch’s t-tests, which do not assume equal  
292 variance, to identify significant differences between  $\log_{10}(x + 1)$  transformed  $B_{i,j}$  of sites  
293 dominated by forest, grassland, pasture/orchard, non-irrigated agriculture, and urban landscapes,  
294 and averages of all samples within each month. The locations with surrounding land cover  
295 dominated by saltwater (n=1) and freshwater (n=2) were excluded due to low replication.

296

## 297 **RESULTS**

298 Mean flying insect biomass was 2,329 mg/day  $\pm$  79 SE across all sampling periods and trap  
299 locations and varied from 0 to 17,543 mg/day. On average across traps, biomass increased from  
300 734 mg/day  $\pm$  98 SE in early April, to a peak of 5,356 mg/day  $\pm$  401 SE in late June, declining to  
301 568 mg/day  $\pm$  111 SE in late October. Flying insect biomass was strongly predicted by  
302 temperature, latitude, precipitation, percent forest cover, and sampling period (Table 1). AIC<sub>c</sub>  
303 model comparison selected three top models which always included the 2<sup>nd</sup> degree polynomial of  
304 sampling period, the 2<sup>nd</sup> degree polynomial of average monthly maximum 2019 temperature, and

305 negative effects of  $\Delta$  temperature from the long-term average, latitude, monthly precipitation,  
306 and percent forest cover (Appendix 1: Table S1). The second and third top models additionally  
307 included a negative effect of percent urban cover and a positive effect of percent pasture/ orchard  
308 cover (Appendix 1: Table S2). However, these models did not greatly improve  $R^2$  or log-  
309 likelihood; thus these two land cover types provided only weak additional explanatory power  
310 (Arnold, 2010). Elevation did not appear in any top models (Appendix 1: Table S1). The top  
311 model explained 51% of the variance in flying insect biomass without location information  
312 (marginal  $R^2$ ) and 74% of flying insect biomass was accounted for when including the random  
313 effect of location identity (conditional  $R^2$ ; Appendix 1: Table S1).

314

### 315 *Climate and latitude*

316 Flying insect biomass increased with mean monthly maximum temperature within 2019  
317 sampling (Table 1, Fig. 2A), and declined with increasing latitude (Table 1, Fig. 2B) and  
318 monthly cumulative precipitation (Table 1, Fig. 2C). While 2019 mean monthly maximum  
319 temperature was included in all top models, only the first order polynomial term was significant,  
320 suggesting the effect was linear (Table 1; Appendix 1: Table S2). When included in the same  
321 model as 2019 monthly maximum temperature, the  $\Delta$  temperature had a negative effect on flying  
322 insect biomass (Table 1; Fig. 2D). Across the 48 sites in which sampling occurred in all seven  
323 months (Apr. - Oct.), an interaction between growing season temperature and latitude was  
324 predictive of flying insect biomass (Appendix 1: Table S3;  $F_{3,44} = 4.3$ ,  $R^2 = 0.23$ ,  $P = 0.01$ ). The  
325 effect of growing season temperature on flying insect biomass increased from a negative  
326 temperature effect at lower latitudes to a positive effect at higher latitudes (Fig. 3).

327

### 328 *Land cover*

329 Flying insect biomass declined with increasing percent forest cover and tended to decrease with  
330 percent urban cover and increase with percent pasture/orchard (Appendix 1: Table S2).

331 Categorizing trap locations by dominant land cover showed grassland/shrubland locations to  
332 generally have the highest biomass in the early-mid growing season (Fig. 4C), and a moderate  
333 increase in biomass in non-irrigated cropland across the growing season (Fig. 4E). However,  
334 neither percent grassland/shrubland nor percent non-irrigated cropland explained variation in  
335 biomass after accounting for seasonality and temperature (Appendix 1: Table S1). Urban-  
336 dominated sites tended to have slightly higher catches of biomass within months (Fig. 4F), but  
337 this may be due to the six urban-dominated sites all being located in southern Germany (Fig. 1).  
338 When included in the full model with temperature variables, flying insect biomass was weakly  
339 negatively correlated with percent urban cover (Appendix 1: Table S2A).

340

## 341 **DISCUSSION**

342 In this first outcome of the German Malaise Trap Program, we found flying insects to be  
343 extremely sensitive to temperature, with both a positive effect of monthly temperature and a  
344 negative effect of 2019 temperatures exceeding long-term averages predicting daily sampled  
345 biomass. Across all sampling, flying insect biomass increased linearly with temperature in  
346 contrast to the unimodal relationship predicted by our first hypothesis. However, in support of  
347 our second hypothesis, the relationship between temperature and flying insect biomass shifted  
348 from positive in colder locations in northern Germany to negative in warmer locations in

349 southern Germany. Additionally, precipitation had a negative relationship with flying insect  
350 biomass, in support of our third hypothesis. Finally, we did not find strong support for our fourth  
351 hypothesis that more heavily-human impacted land use types would have the lowest biomass  
352 with locations surrounded by pasture/orchard, grassland, and non-irrigated agriculture tending to  
353 have higher insect biomass than those surrounded by forests or urban areas.

354

### 355 *Temperature*

356 Temperature effects on ectothermic insects can manifest directly on individuals' metabolism,  
357 growth, reproduction, immunity, survival, behavior, and dispersal (Sinclair *et al.*, 2016; Harvey  
358 *et al.*, 2020), and through effects on other trophic levels such as through altering plant biomass,  
359 plant quality, or active time-periods of natural enemies (Laws & Joern, 2013; Kwon *et al.*, 2019;  
360 Thakur, 2020). Our results suggest an overall positive linear effect of temperature on flying  
361 insect biomass across Germany. The lack of a unimodal relationship between temperature and  
362 insect biomass may be a result of the coarse taxonomic (flying insects caught in malaise traps)  
363 and temporal (two week) resolution of our samples in comparison to other studies (e.g. Kühnel &  
364 Blüthgen, 2015). However, we additionally detected a negative effect of the  $\Delta$  temperature (2019  
365 temperatures minus the colder long-term average), and the slope of the relationship between  
366 temperature and flying insect biomass declined as temperatures declined at the lower latitudes,  
367 which tended to be the warmest locations in 2019. Hallmann *et al.* (2017) found a positive effect  
368 of temperature on insect biomass; however, biomass loss over time was greatest in the middle of  
369 the growing season, when temperatures are highest. A decelerating benefit of temperature in  
370 regions with greater increases in temperature is consistent with a study of two surveys of ant  
371 communities across North America that were conducted 20 years apart, which found that sites



372 with the largest increases in average temperature had the largest declines in colony density  
373 (Kaspari *et al.*, 2019). We predict future monitoring will detect increasingly negative effects of  
374 temperature due to ongoing climate warming, as temperature begins to exceed species' optimum  
375 temperature ranges.

376

### 377 ***Precipitation***

378 We detected a negative effect of precipitation on flying insect biomass. As our study covered  
379 only one growing season, our result likely reflects direct insect mortality from heavy rain or  
380 reduced flight activity. Insects can detect changes in barometric pressure and will stop flying if  
381 they sense storms approaching (Pellegrino *et al.*, 2013). Future investigations of the German  
382 Malaise Trap Program can examine long-term effects of changing precipitation regimes on  
383 insect populations which may manifest through indirect paths, including through altering plant  
384 biomass (Prather *et al.*, 2020), plant phenology (Jamieson *et al.*, 2012), nutrient availability in  
385 host plants and nectar (Eisikowitch & Woodell, 1975; Welts *et al.*, 2020b), pollen availability  
386 (Ortega *et al.*, 2007), the efficacy of chemical signals used by insects (Lawson & Rands, 2019),  
387 and the moisture and other properties of soils where many insects overwinter (Yang *et al.*, 2018).

388

### 389 ***Land cover***

390 Land cover change and intensification of human land use, resulting in loss and reduced quality of  
391 habitat, is likely a major contributor to insect decline (Potts *et al.*, 2010; Winfree *et al.*, 2011;  
392 Díaz *et al.*, 2019) with ~75% of global land significantly altered by human activities (IPBES,  
393 2019). In contrast to our hypothesis, we detected only weak effects of urban and agricultural land

394 cover on flying insect biomass. This may be due in part to a minority of heavily human-impacted  
395 land cover surrounding our sites, especially with regards to intensive agriculture. While the  
396 percent urban area surrounding the trap location had only a slight negative effect on flying insect  
397 biomass, urban areas may alter insect communities in other ways, such as through species  
398 composition (Theodorou *et al.*, 2020). Higher temperatures in urban areas compared to their rural  
399 surroundings may partly compensate for lower habitat quality and explain the above average  
400 biomass in spring and late summer/autumn in the urban areas investigated in our study.

401         Even within one land-cover type, large variability exists in habitat quality. This is  
402 particularly true of urban areas and agricultural land, which range from large paved urban areas  
403 and areas with intensive pesticide use to urban gardens and low intensity organic farms which  
404 can provide high quality habitat for insects (Bengtsson *et al.*, 2005; Hausmann *et al.*, 2020).  
405 While moderately impacted by human activity, non-irrigated agricultural areas, pasture land, and  
406 orchards in this study tended to support higher biomass, suggesting these land use types may  
407 provide suitable habitats for Germany's flying insects. Alternatively, fertilization and the  
408 prevalence of monoculture on conventional farms may increase insect biomass through  
409 alleviating nutrient limitation and providing high concentrations of host plants, while not  
410 benefiting insect biodiversity (Root, 1973; Haddad *et al.*, 2000).

411         We detected reduced insect biomass in trap locations surrounded predominantly by  
412 forests. Forests may provide fewer floral resources than open fields (Jachula *et al.*, 2017).  
413 Alternatively, the vegetation structure in forests may limit insect movement through the  
414 landscape, reducing trap catch in comparison to more open systems like grasslands (Cranmer *et*  
415 *al.*, 2012). However, this result is in contrast to previous work, albeit using different sampling  
416 methods, showing high Lepidoptera biomass coming to light traps in forests compared to other

417 land use types in the UK (Macgregor *et al.*, 2019), and higher flying insect biomass with  
418 increasing forest cover in a study using car-mounted nets in Denmark (Svenningsen *et al.*, 2020).  
419 Our malaise-trapping methods are more directed toward Hymenoptera and Diptera, and towards  
420 the lower canopy, potentially contributing to this discrepancy.

421

#### 422 ***Comparison with Hallmann et al. 2017***

423 Average flying insect biomass captured in Hallmann *et al.* (2017) varied from 9,192 mg/day in  
424 1989 to 2,531 mg/day in 2016 (mean of within-month sample means for May-Sept; April  
425 excluded as no April 1989 sampling was conducted). In comparison, our traps collected a  
426 monthly average of 2,404 mg/day in May-Sept. However, the malaise traps used in Hallmann *et*  
427 *al.* (2017) were ~51% larger (Hallmann *et al.* [2017] trap opening dimensions per side: 1.79 m<sup>2</sup>,  
428 traps used in this study: 1.16 m<sup>2</sup>). If trap opening has an appreciable positive effect on trap catch,  
429 this suggests higher trap catch in this study compared to the last sampling year in Hallmann *et al.*  
430 (2017). This discrepancy is most likely due to the difference in sampling locations between the  
431 studies, but we cannot rule out an increase in biomass of flying insects in Germany.

432

#### 433 ***Caveats***

434 Insect biomass is a common currency ecosystem-level measure of insect productivity and is an  
435 index of energy availability for higher trophic levels. Nonetheless, we cannot differentiate  
436 variation in abundance, body size, species diversity, or dominance from biomass data alone.  
437 High temperatures may reduce average insect body size either by causing smaller adult body  
438 sizes within species (Atkinson, 1994; Klockmann *et al.*, 2017; Polidori *et al.*, 2020) or by

439 favoring smaller species (Bergmann, 1848; Daufresne *et al.*, 2009; Merckx *et al.*, 2018). While  
440 one long-term study of flying insects in the Netherlands found no evidence of higher rates of  
441 decline in larger species over the past two decades (Hallmann *et al.*, 2020), larger-bodied species  
442 may have become rare earlier in the last century (Seibold *et al.*, 2015). Climate and land-cover  
443 change may otherwise alter insect communities by favoring particular trophic levels (Agosta *et*  
444 *al.*, 2018; Welts *et al.*, 2020a), invasive species (Ju *et al.*, 2017), or pest species with outbreak  
445 dynamics (Bernal & Medina, 2018). Furthermore, insect responses to climate and land cover  
446 may vary with microhabitat preference (Suggitt *et al.*, 2018). For example, flying insects may be  
447 more affected by rising temperatures than other insects as they cannot buffer high temperatures  
448 by burrowing in soil or plant tissue (Baudier *et al.*, 2015; Wagner, 2020).

449

#### 450 ***Future directions***

451 With several notable exceptions including mosquito and ground beetle monitoring by the US  
452 National Ecological Observation Network (Thorpe *et al.*, 2016; Blair *et al.*, 2020), and regional-  
453 scale monitoring programs of butterflies and macro-moths (e.g. Kühn *et al.*, 2008; Dennis *et al.*,  
454 2019; van Swaay *et al.*, 2019; Wepprich *et al.*, 2019), spatially distributed observational  
455 monitoring efforts of multiple biological taxa have tended to target plants and vertebrates but not  
456 insects (Eggleton, 2020). Limited large-scale, long-term standardized insect monitoring is one  
457 reason for low power in our ability to disentangle different potential drivers of insect decline, and  
458 understand how this varies with region. Empirical studies of insect communities often lack the  
459 spatial coverage needed to be broadly representative or to test for variation due to land cover  
460 types (but see Jeliazkov *et al.*, 2016; Wepprich *et al.*, 2019). Meta-analyses have large spatial  
461 coverage, but can be subject to site and/or publishing bias and must reckon with variation in

462 research goals and methodology (Gurevitch & Mengersen, 2010). Thus more distributed,  
463 standardized, and continuous insect monitoring programs are needed to fill gaps in current  
464 knowledge of temporal insect population and community dynamics (Cardoso & Leather, 2019).

465         The German Malaise Trap Program helps to fill this gap for Germany through both  
466 continued monitoring of flying insect biomass and recently begun DNA metabarcoding. A major  
467 advantage of using LTER and National Natural Landscape sites is that they are well established  
468 and managed by personnel with excellent knowledge of the respective site. As the European  
469 LTER network (eLTER RI; Mirtl *et al.*, 2018) was recently accepted by the EU as part of the  
470 European Research Infrastructure Roadmap (ESFRI), stronger linkages between the more than  
471 400 European LTER sites are currently being established. One major goal is to standardize and  
472 harmonize long-term biodiversity monitoring across Europe (Haase *et al.*, 2018) with malaise  
473 traps currently being considered as a potential European biodiversity standard observation, and  
474 the German Malaise Trap Program providing a blueprint. Future work aims to answer how flying  
475 insects will respond to climate and land cover change over the long-term. Finally, continued  
476 monitoring by the German Malaise Trap Program will advance our understanding of trends on  
477 spatial-temporal scales that are lacking in previous studies on insects (Didham *et al.*, 2020), and  
478 in productivity/biodiversity trends more generally (McGill *et al.*, 2015).

479

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809

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820



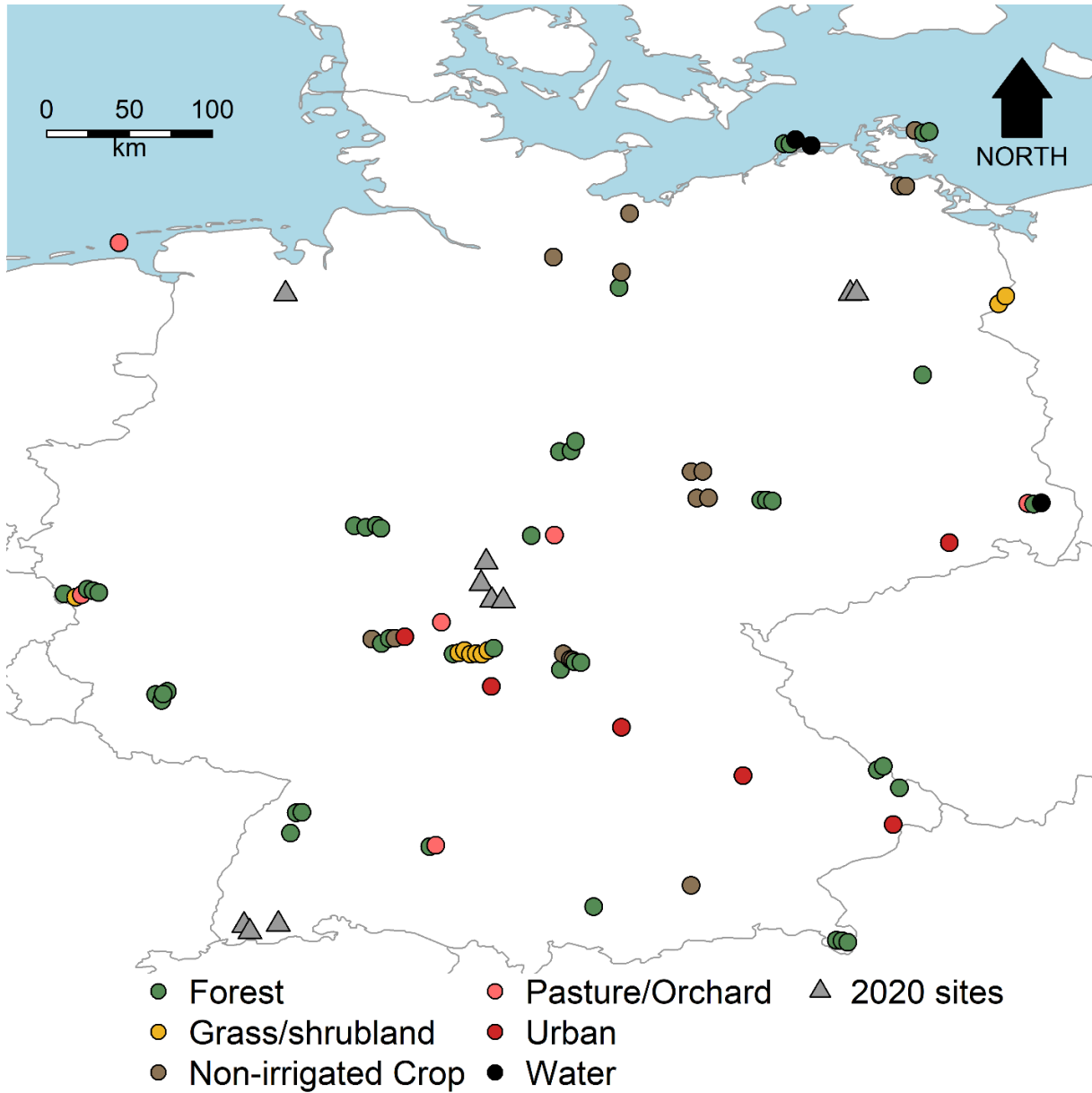
821 **Table**

822 **Table 1. Top AIC<sub>c</sub> model of predictors of flying insect biomass.** Model includes the random  
823 variable of trap location. T-tests use Satterthwaite's method. Poly(X,1) indicates the first-order  
824 term of the 2<sup>nd</sup> degree polynomial for variable X, while poly(X,2) indicates the second-order  
825 term of the 2<sup>nd</sup> degree polynomial. Predictor variables are defined in the Materials and Methods.  
826 Model characteristics include estimate (Est), standard error (SE), degrees of freedom (df), t-  
827 value, and p-value (*P*).

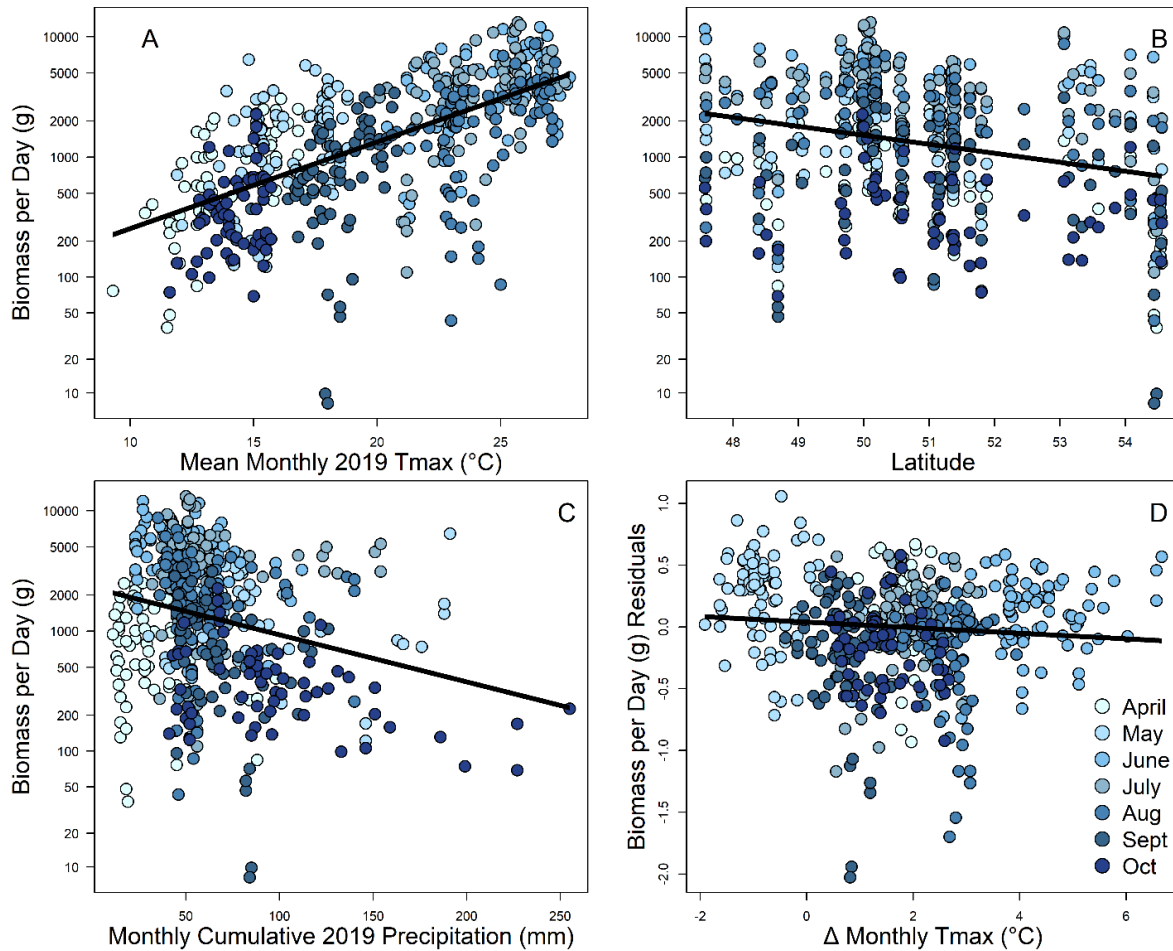
	<b>Est</b>	<b>SE</b>	<b>df</b>	<b>t-value</b>	<b><i>P</i></b>
Intercept	7.84	0.95	89.46	8.24	< 0.001
% forest	-0.33	0.10	87.6	-3.31	0.001
latitude	-0.09	0.02	87.51	-4.79	< 0.001
poly(period,1)	-3.30	0.39	981.7	-8.56	< 0.001
poly(period,2)	-4.02	0.81	1011	-4.94	< 0.001
poly(tmax,1)	8.05	0.97	1017	8.34	< 0.001
poly(tmax,2)	0.21	0.35	961	0.59	0.55
precip	-0.13	0.04	1006	-2.96	0.003
Δtemp	-0.01	0.003	990.5	-3.81	< 0.001

828

829 **Figures**



831 **Figure 1. Map of sampling locations.** Malaise trap locations where samples were collected  
832 beginning in 2019 are depicted as filled circles and color-coded by the dominant land cover in  
833 the surrounding 1 km. Points coded as grey triangles indicate trap locations at which sampling  
834 began in 2020 and are not included in the analyses. Overlapping locations were jittered  
835 longitudinally to improve visualization.



836

837 **Figure 2. Responses of flying insect biomass to the climate variables and latitude.** Each point

838 represents the biomass at each site within each month ( $B_{i,j}$  as calculated by Eq. 1). Across all

839 months and site combinations, flying insect biomass increased with mean monthly 2019

840 maximum temperature (A), and decreased with latitude (B) and cumulative monthly 2019

841 precipitation (C). The response of flying insect biomass to  $\Delta$ temp shifted from positive when

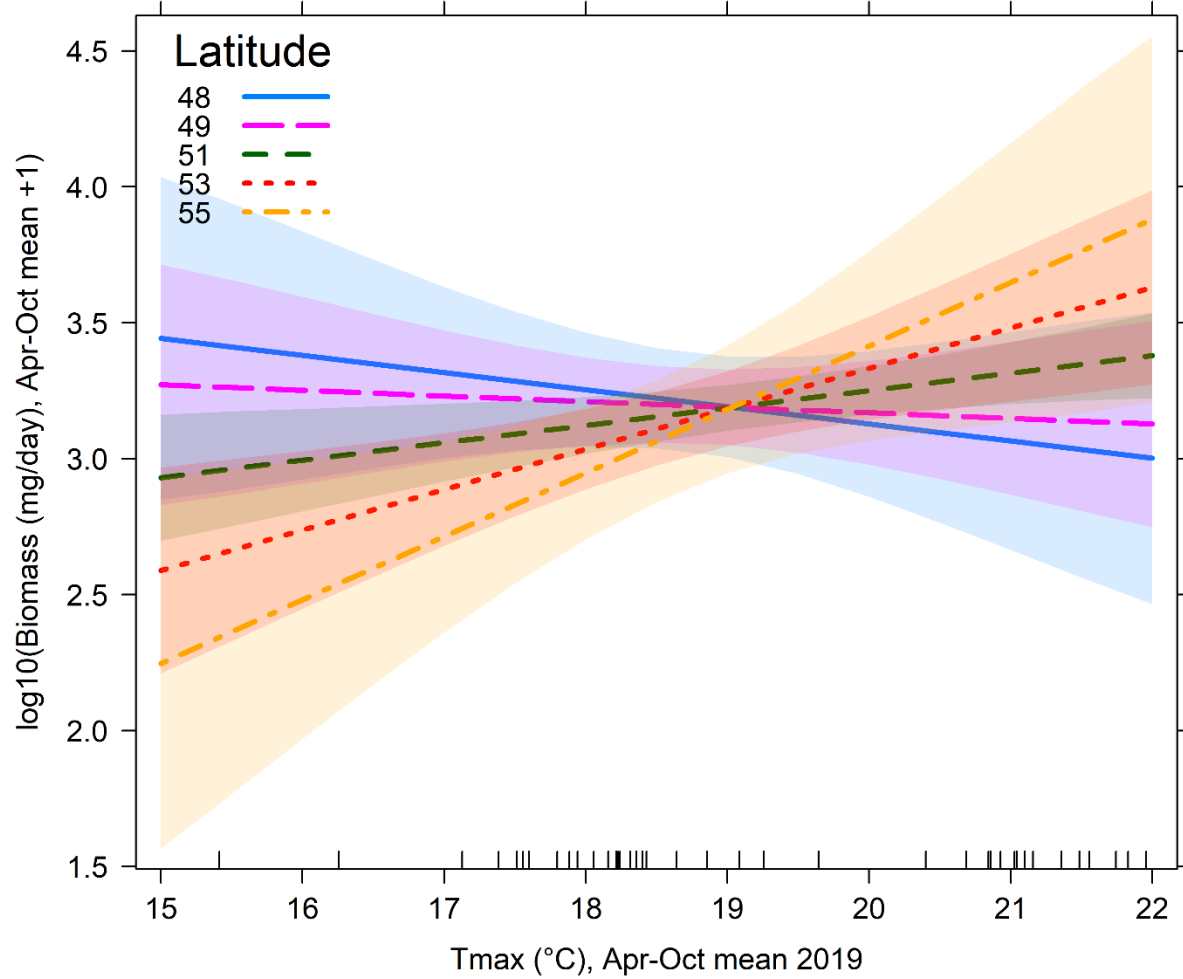
842 examined alone to a negative when the effect of 2019 tmax was included in the model. We

843 therefore used the residuals of the relationship between biomass and 2019 tmax as our response

844 variable to show the negative relationship between insect biomass and  $\Delta$ temp evident in the top

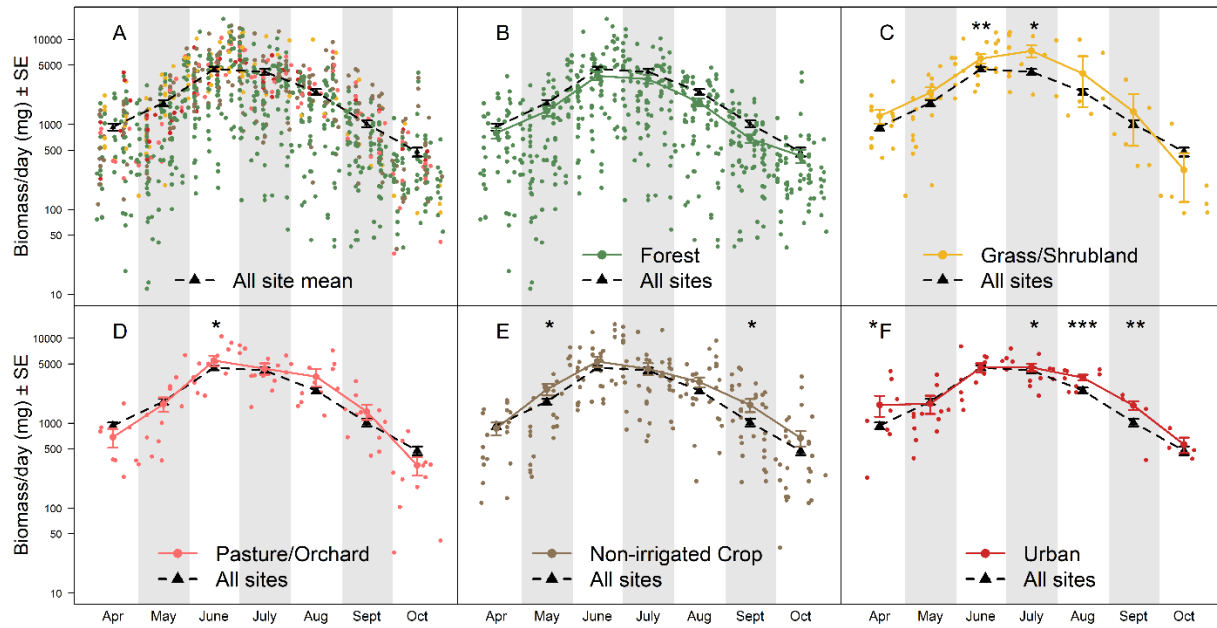
845 AIC<sub>c</sub> model (Table 1) (D).





846

847 **Figure 3. The effect of temperature on flying insect biomass across latitude.** The effect of  
848 temperature shifted from negative to positive with increasing latitude across the 48 sites with  
849 sampling in all 7 months (Apr.-Oct. 2019). Model coefficients are provided in Table S2.



850

851 **Figure 4. Flying insect biomass over the growing season by dominant land cover.** Biomass  
852 (mg/day) over the median sampling day across all 84 trap locations (A), and comparisons  
853 between all locations and locations with surroundings dominated by forests (B),  
854 grassland/shrubland (C), pasture/orchard (D), non-irrigated cropland (E), and urban  
855 environments (F). Point colors in panel A match the dominant land category following colors in  
856 panels B-F. Mean and standard error are provided for biomass within each land cover category  
857 and month. Stars indicate significant differences within each month based on Welch's t-tests  
858 between biomass from dominant land cover categories and all site averages (\* =  $0.05 > P > 0.01$ ,  
859 \*\* =  $0.01 > P > 0.001$ , \*\*\* =  $P < 0.001$ ).

## **Appendix 1:** Climate, latitude, and land cover predict flying insect biomass across a German malaise trap network

### **Contents:**

Table S1-S3

Fig. S1-S4

**Table S1. Top AIC models ( $\Delta AIC_c < 2$ ) of predictors of flying insect biomass.** All models included the random variable of trap identity. Int=intercept, poly(X,1) indicates the first-order term of the 2<sup>nd</sup> degree polynomial for variable X, while poly(X,2) indicates the second-order term of the 2<sup>nd</sup> degree polynomial. Predictor variables are defined in the Methods. Marg R<sup>2</sup>= marginal R<sup>2</sup> or the percent variance explained by the fixed effects, Cond R<sup>2</sup>= conditional R<sup>2</sup> or the percent variance explained by the fixed effects plus the random effect of trap, df= degrees of freedom, logLik= log likelihood,  $\Delta = \Delta AIC_c$ , w= model weight. For summary tables of the top model, see Table 1. For summary tables of the second and third top models, see Appendix 1: Table S2.

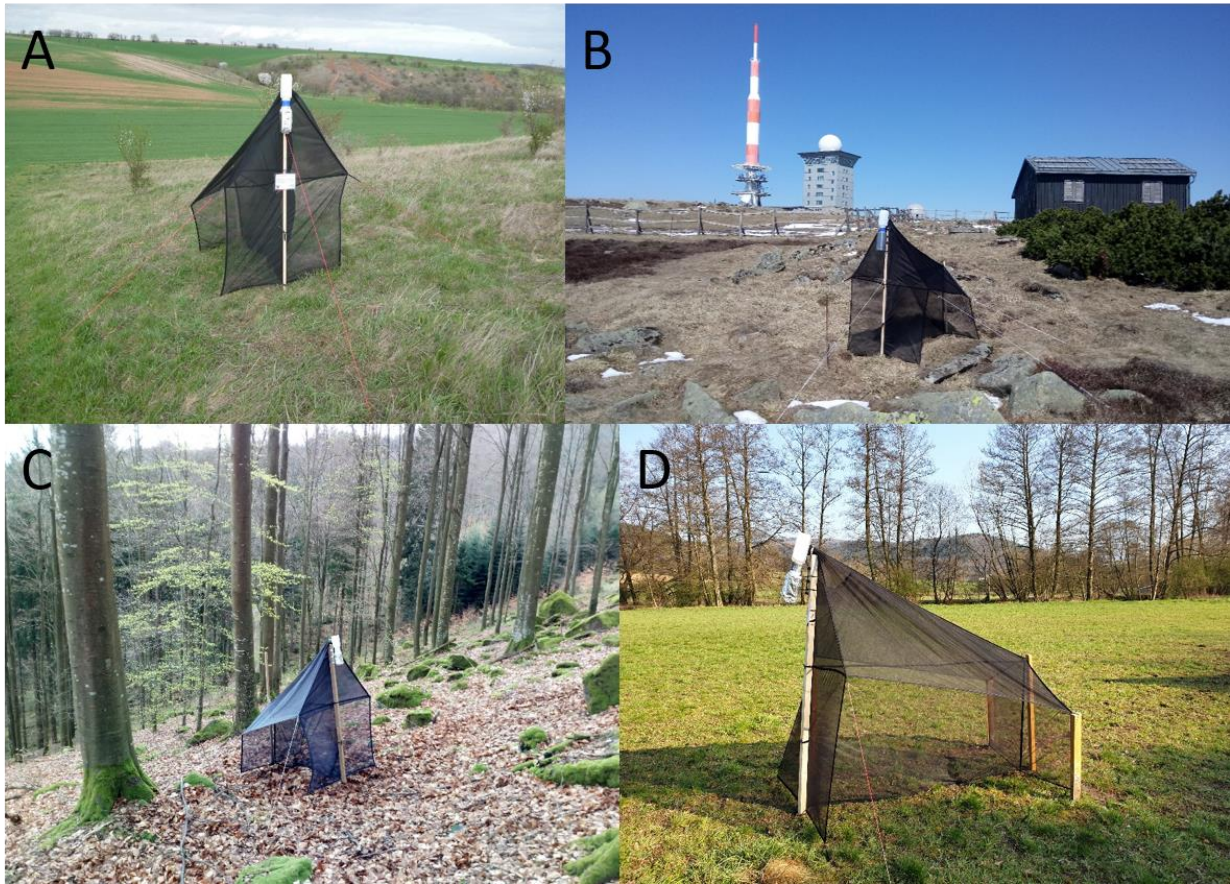
Int	latitude	poly (period,2)	poly (tmax,2)	$\Delta$ temp	precip	%forest	%urban	%pasture/ orchard	Marg R <sup>2</sup>	Cond R <sup>2</sup>	df	logLik	AICc	$\Delta$	w
7.84	-0.088	+	+	-0.0124	-0.131	-0.328			0.51	0.74	11	-364.35	751	0	0.147
8.26	-0.095	+	+	-0.0126	-0.133	-0.402	-0.405		0.52	0.74	12	-363.55	751.4	0.44	0.118
7.81	-0.089	+	+	-0.0125	-0.131	-0.292		0.253	0.51	0.74	12	-364.3	752.9	1.94	0.056

**Table S2. Summary tables of the second (A) and third (B) mixed effects models included in top AIC<sub>c</sub> models (Table S1).** A summary table of the top model is provided in Table 1. All models contain the random variable of trap identity. T-tests use Satterthwaite's method. See Methods and Table 1 caption for variable explanations. Model characteristics include estimate (Est), standard error (SE), degrees of freedom (df), t-value, and p-value (*P*).

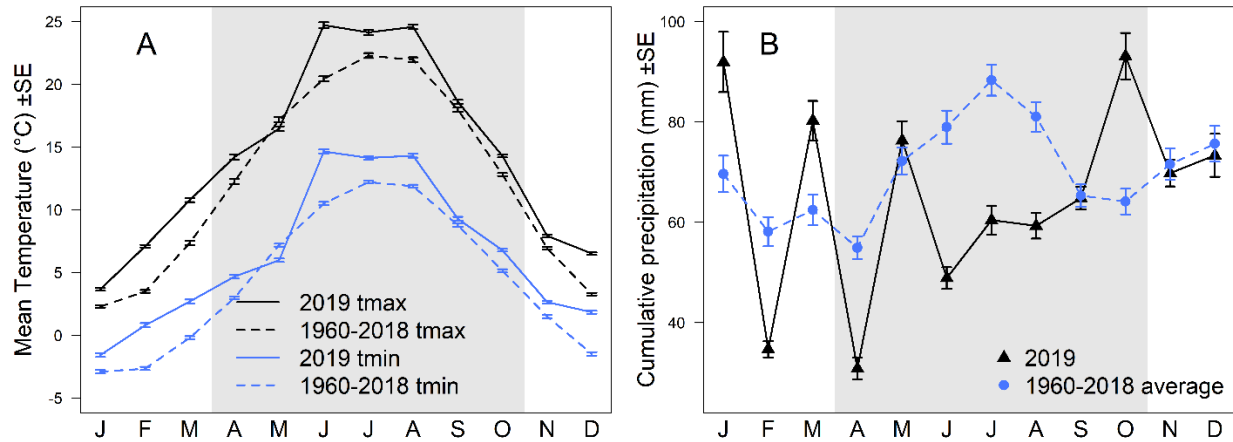
	Est	SE	df	t-value	<i>P</i>
<b>A.) Model 2</b>					
Intercept	8.26	0.98	87.66	8.43	< 0.001
%forest	-0.40	0.11	83.87	-3.7	< 0.001
latitude	-0.10	0.02	86.01	-5.07	< 0.001
poly(period,1)	-3.30	0.39	982.1	-8.55	< 0.001
poly(period,2)	-3.99	0.81	1011	-4.91	< 0.001
poly(tmax,1)	8.10	0.97	1016	8.39	< 0.001
poly(tmax,2)	0.22	0.35	960.2	0.63	0.53
precip	-0.13	0.04	1006	-2.99	0.003
Δtemp	-0.01	0.003	989.9	-3.86	< 0.001
%urban	-0.40	0.26	84.52	-1.59	0.12
<b>B.) Model 3</b>					
Intercept	7.81	0.95	88.53	8.21	< 0.001
%forest	-0.29	0.10	87.4	-2.80	0.006
latitude	-0.09	0.02	86.39	-4.81	< 0.001
%pasture/orchard	0.25	0.23	80.44	1.09	0.28
poly(period,1)	-3.32	0.39	979.9	-8.59	< 0.001
poly(period,2)	-3.98	0.81	1009	-4.89	< 0.001
poly(tmax,1)	8.10	0.97	1015	8.38	< 0.001
poly(tmax,2)	0.20	0.35	961	0.59	0.56
precip	-0.13	0.04	1006	-2.94	0.003
Δtemp	-0.01	0.003	989.5	-3.84	< 0.001

**Table S3. Model coefficients for the interaction between monthly temperature and latitude (Fig. 3).** While individual model coefficients were all marginally significant, the full model predicted 23% of the variation in average biomass (mg/day) averaged across the seven sampling months for the 48 sites with sampling in all months ( $F_{3,44} = 4.3$ ,  $R^2 = 0.23$ ,  $P = 0.01$ ). GST= growing season temperature, the average temperature for each site from Apr-Oct 2019. Model characteristics include estimate (Est), standard error (SE), degrees of freedom (df), t-value, and p-value ( $P$ ).

	<b>Est</b>	<b>SE</b>	<b>t-value</b>	<b>P</b>
Intercept	43.1	21.65	1.99	0.053
GST	-2.1	1.17	-1.8	0.079
Latitude	-0.81	0.42	-1.91	0.063
GST * Latitude	0.04	0.02	1.86	0.07

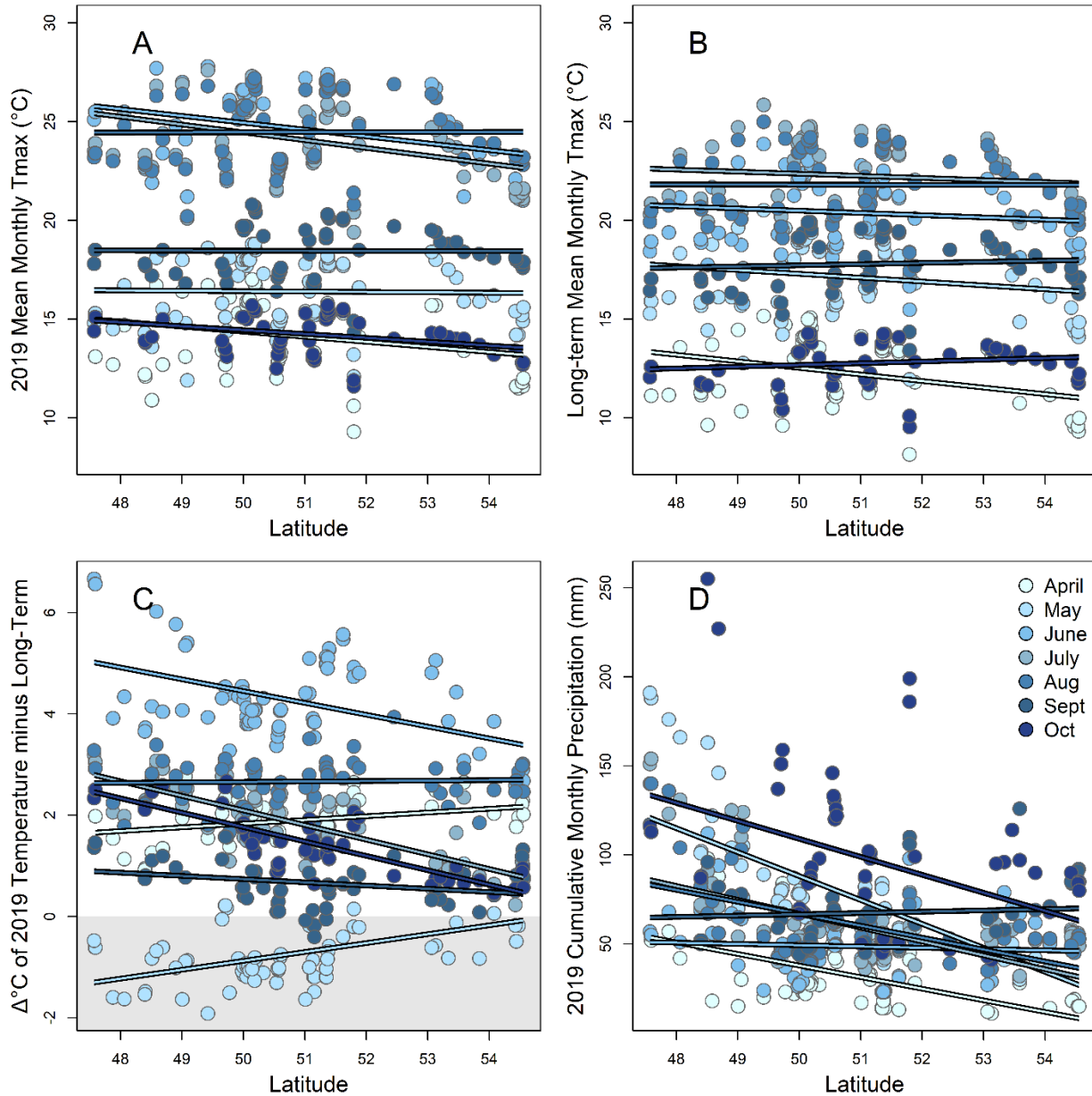


**Figure S1.** Examples of traps running in 2019 as part of the German Malaise Trap Program. Photos show traps at the LTER site Tereno- Friedeburg (A; photo credit: Mark Frenzel), at the Harz National Park (B; photo credit: Andreas Marten), at the Black Forest National Park (C; photo credit: Jörn Buse), and at the LTER site Rhine-Main-Observatory (D; photo credit: Peter Haase).

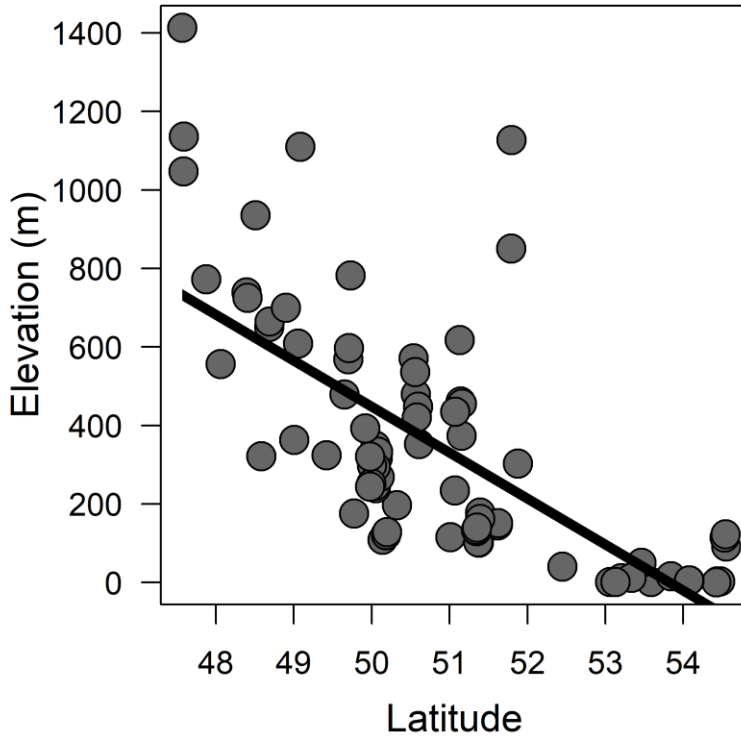


**Figure S2.** Comparison of climate at the 84 trap locations between 2019 and long-term average (1960-2018) including the average maximum monthly temperatures (tmax) and minimum monthly temperatures (tmin) in °C ± standard error (A) and cumulative monthly precipitation in mm ± standard error (B). Period of the year in which malaise trap sampling occurred is shaded in grey.





**Figure S3.** Changes with latitude across our 84 trap locations in 2019 mean monthly maximum temperature (A), the 1960-2018 long-term average monthly maximum temperature (B), the change in 2019 mean monthly maximum temperature minus the 1960-2018 long-term average (C), and 2019 cumulative monthly precipitation (D). Each point represents one month at one location, and only month/location combinations from which flying insect biomass data were collected are included. Across all months, 2019 mean monthly maximum temperature showed a weak trend to decrease with latitude (A;  $F_{1,520} = 3.6$ ,  $R^2 = 0.01$ ,  $P = 0.06$ ), while the 1960-2018 long-term average monthly maximum temperature did not vary with latitude (B;  $F_{1,520} = 1.6$ ,  $R^2 < 0.01$ ,  $P = 0.21$ ). While varying with month, the average  $\Delta$  °C of 2019 maximum temperature over the long-term average decreased with latitude (C;  $F_{1,520} = 6$ ,  $R^2 = 0.01$ ,  $P = 0.01$ ), as did cumulative monthly precipitation (D;  $F_{1,520} = 60.6$ ,  $R^2 = 0.1$ ,  $P < 0.001$ ).



**Figure S4.** Elevation declined with increasing latitude across our 84 trap locations ( $F_{1,82} = 74.5$ ,  $R^2 = 0.48$ ,  $P < 0.001$ ).