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10 **Microclimatic buffering in forest, agricultural and urban landscapes through the lens of**
11 **a grass-feeding insect**

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36Open Research Statement:

37Upon acceptance, data and R-code that support the findings will be permanently available in

38Dryad data repository via the following link: [hyperlink to dataset will be provided here]. No

39novel code was used for statistical analysis. If deemed necessary, Subject-matter Editor may

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44ABSTRACT

45For small, ectotherm species, dealing with microclimatic variation during sensitive stages of
46their development is a critical component of their ecological interactions within and among
47different landscape settings. However, it is often unknown whether the use of habitats in
48different landscape settings may affect microclimatic conditions at the level of microhabitats
49(e.g. at host plants for herbivorous insects). As opposed to standard ecological monitoring
50experiments, we aim to identify the microclimatic offsets that accurately represents the
51environment in which a small arthropod spend most of its life. As a case study, we selected
52grassy sites that corresponded to the microhabitat of grass-feeding insects in general, and
53larvae of the butterfly *Pararge aegeria* in particular as this insect recently expanded its habitat
54use from forest (edges) to agricultural and urban environments. We tested to what extent local
55microclimates and microclimatic buffering capacity differed between tufts of grass in forest
56and in two anthropogenic (i.e. agricultural and urban) landscape settings by measuring
57microclimatic variables with sensors at the level of the grasses. We compared temperature,
58relative humidity and vapour pressure deficit (VPD) during an exceptionally warm and dry
59summer period with parallel data from weather stations and tested for differences between
60microclimatic profiles among the three landscape settings. Microclimatic conditions
61corresponded only partly to variables based on weather station data. Differences were
62particularly significant for relative humidity and VPD, but not for day and night temperature.
63Effects of canopy openness on the variability of microclimatic variables were landscape-
64specific. Host plants in agricultural settings experienced strong microclimatic fluctuations and
65low short-term variability in VPD. In urban settings, urban heat island effects increased night
66temperature, but also showed microclimatic buffering effects similar to the ones in forest
67settings. Our findings stress the functional implications of landscape-specific microclimatic
68profiles at the appropriate organism-centred scale. We discuss the significance of such

69microclimatic profiles for ecological studies dealing with ectotherms under climate and land
70use change.

71INTRODUCTION

72Structural habitats (e.g. particular woodland types) have often been assumed to be functional
73habitats for particular species based on the simple presence of the species. Environmental
74correlates of presence-only distribution data help our understanding of the complex nature of
75a species' habitat. Hence, such information has frequently been used to make future range
76predictions under different scenarios of climate change. However, the very same structural
77habitat may provide different thermal conditions at different latitudes (or under different
78levels of climate change). Thermophilous ectotherms may occupy, for example, sandy or
79rocky habitats in the north of Europe, grassy or shrubby habitats at intermediate latitude and
80forest habitats in the south of Europe (e.g., Grayling butterfly *Hipparchia semele*; Tropek et
81al. 2017). Hence, the organism may find its functional habitat in different structural habitats
82under different macroclimatic conditions (Van Dyck 2012). Moreover, although niche
83conservatism (i.e., the tendency of species to retain ancestral ecological characteristics) has
84often been assumed for species with a specific affiliation with a particular habitat type (Wiens
85& Graham 2005), modifications in resource-use and in habitat-use have been documented in
86species that deal successfully with rapidly changing anthropogenic landscapes. Examples
87include *Turdus merula* blackbirds that expanded their use of woodland habitat into urban
88environments (Evans et al. 2009) and *Aedes aegypti* mosquitoes that expanded their habitat
89use from African forests into domestic habitats throughout the world (Xia et al. 2021). In the
90latter case, females switched their larval sites from natural water containing tree holes to
91artificial containers like clay pots, which provides multiple opportunities for range expansion.

92Understanding how living conditions of species alter in response to human-induced rapid
93environmental change requires the study of the combined effects of climate and landscape-
94scale habitat availability (Wilson et al. 2010). The majority of animal species are small-sized
95terrestrial insects (Wilson, 1992), which have complex life cycles and whose larvae develop

96in close interaction with the (thermal) environment on a small scale (Dillon et al., 2016;
97Pincebourde et al., 2016; Pincebourde & Woods, 2012, 2020). Although the role of
98microclimates for understanding the ecology of insects have long been acknowledged
99(Willmer, 1982), few studies have looked at how dominant structural habitats at the landscape
100scale may affect temperature and humidity experienced by such organisms at fine resolution
101(e.g. on their host plants).

102A bottom-up, resource-based approach to identify a species' functional habitat within and
103across different structural habitat types (i.e. land cover types) has been shown to be a much
104more appropriate way to conceive habitat in insects, than the much more widespread, top-
105down structural habitat or biotope-based approach (Dennis et al. 2003; Turlure et al. 2019).
106This is true for both fundamental and applied ecological studies that need to understand and
107delineate a species' habitat (Van Dyck 2012). This matter has been particularly addressed for
108species of conservation interest (e.g. glacial relict species that rely as larva on microclimatic
109buffering of specific components of the vegetation within structural habitat types; Turlure et
110al. 2010). We argue that it may be equally important for understanding how successful,
111rapidly spreading species are able to deal with microclimatic conditions in different structural
112habitats. As has been shown for forest species in bees, dung beetles and dipterans, light and
113microclimate conditions provided by local woodlots may indicate suitable habitat,
114independent of landscape composition of the wider landscape (Williams & Winfree, 2013;
115Righi et al., 2018).

116Grass-feeding insects that make use of a number of widely distributed grass species that occur
117under a range of environmental conditions (i.e. both within and outside forest), may be such
118an example. For species with such an ecological profile, structural habitat-based approaches
119do not grasp well their functional habitat. Here, we address the issue of microclimatic
120variation at the level of grasses that grow under a range of environmental conditions within

121and outside forest. This approach is of general interest to larger communities of grass-feeding
122insects. Here, we are particularly interested in testing its significance within the context of an
123insect that recently expanded its ecological niche and habitat use from forest to different types
124of more open, anthropogenic environments. We tested for microclimatic differences between
125ancestral habitat (i.e. forest) and two recently colonized environments (i.e., agricultural and
126urban landscape settings) in the case of the Speckled Wood (*Pararge aegeria*).

127We focus on microclimate variables, i.e. at the level of the host grass species that grow in the
128grass layer accompanied by nearby canopy. On the one hand, nearby woodlots may provide
129microclimatic conditions that protect larval stages and grass blades from heat stress,
130regardless of the nature of the wider landscape. At the level of the host plant, even small
131nearby woodlots could provide shade, block wind and retain outgoing radiation (Geiger et al.,
1322003; Süle et al, 2020). However, on a landscape scale, forest, agricultural and urban climatic
133conditions differ significantly: forests typically buffer fluctuations in temperature and
134humidity with effects gradually diminishing towards the forest edges (Lin et al., 2020) and
135cause sub-canopy cooling during summer (Haesen et al., 2021). Agricultural and urban
136landscapes are characterized by more open, early succession environments and smaller,
137dispersed woodlots. The corresponding conditions in these landscapes are generally warmer,
138drier and less buffered (Geiger et al., 2003; Boggs & McNulty, 2010; Ewers & Banks-Leite,
1392013; von Arx et al., 2013; Middel et al., 2015).

140Urban climates are, particularly in temperate-zone regions, generally warmer and dryer than
141surrounding areas because of 1) heat-absorption by building materials with a high heat
142retention capacity, 2) reduction in evaporation and heat-dissipating capacity due to a reduced
143vegetation cover, 3) restricted air circulation because of buildings and 4) ‘waste heat’ caused
144by engines (i.e. Urban Heat Island effect; Arnfield, 2003; Larsen, 2015). This can affect an
145organism in various ways. Relatively warmer conditions in urban habitats may increase

146metabolic rate and, indirectly, available food abundance (Lowe et al., 2014; Serruys & Van
147Dyck, 2014; Merckx et al., 2018; Chick et al., 2021). Urban conditions may also affect heat
148stress risks (Kaiser et al., 2016; Pincebourde et al., 2016). For example, mosquito larvae
149(*Aedes albopictus*) growing in areas that are more exposed to urban heat effects during fall,
150survived better when compared to growing conditions in rural microclimates. During a hot
151summer, however, the effect is reversed (Murdock et al., 2017).

152Although the measurement of VPD has gained much more attention in studies on plant
153microhabitats (Davies-Colley et al., 2000; von Arx et al., 2013; Süle et al., 2020; Aguirre et
154al., 2021), it may also matter for microclimates that affect small organisms like insects. VPD
155is exponentially related to changes in temperature under constant humidity and is regarded as
156the ‘drying power’ of the air on wet surfaces (Monteith & Unsworth, 2013). Measuring such
157‘drying power’ may have significance for understanding how desiccation stress affects growth
158and survival in drought-sensitive ectotherms, either directly (Tarrant & McCoy, 1989; Shipp
159& Gillespie, 1993; Rickards & Boulding, 2015) or indirectly via decreased plant growth
160(Bauerfeind & Fischer, 2013; Massmann et al., 2019). As temporal variation in microclimatic
161conditions may affect the development of traits and life-history decisions in microclimate-
162sensitive ectotherms (Doody et al., 2006; Pincebourde & Woods, 2012; Parmentier et al.,
1632017), we introduced two novel variables other than standard deviation that reflect different
164rates of temporal variation (i.e., short-term variability and day-to-day variability of VPD).
165These variables are assumed to reflect the way caterpillars or other grass-feeding insects
166experience predictability of drought conditions over time. At least in *P. aegeria*, larvae are
167known to use microclimatic information to change developmental strategies accordingly
168(Shreeve, 1986a).

169In this paper, we measured microclimatic conditions at the level of tufts of grasses during
170extremely warm summer. We compared these with standardized measures gathered at nearby

171weather stations and tested whether these differences (i.e. microclimatic effects) differed
172between landscape types. Because all sampled sites had a similar vegetation configuration
173(i.e. grass layer with nearby canopy), we predict that the climatic differences from weather
174station data are larger than the microclimatic differences measured between landscape types.
175Since all weather stations were located in flat, open fields, we also predict that, even when
176controlling for canopy openness, the agricultural microclimate is most similar to the weather
177station measures.

178Secondly, we tested whether the raw climatic measures of a grass habitat in agricultural and
179urban landscape types are different from those of forest habitats, and whether measures
180gathered from these two anthropogenic landscape types differed from each other. We predict
181more extreme temporal variation in temperature and humidity in agricultural settings than in
182forest settings. Levels of temporal variation in urban locations are predicted to be higher
183compared to forest settings (i.e. reduced buffering effect of large-scale canopy cover), but
184lower than agricultural settings (i.e. higher night temperatures in urban landscapes due to the
185urban heat island effect).

186

187**MATERIALS AND METHODS**

188**Sample sites**

189We selected four study areas consisting each of an urban, an agricultural and a forest location
190(latitudinal range: 50° 51' 0" N \pm 6' 0"; study areas: Aalst, Brussels, Leuven and Tienen; see
191Fig. 1). Urban built area of the cities ranges from 13.6 km² (Tienen) to 128.86 km² (Brussels).
192Each of the 12 sample locations were chosen at a 61.8 acres (25 hectares) grid area and were
193characterized by their dominant land cover type (i.e. i) buildings and other impervious
194surfaces, ii) meadows and pastures or iii) tree cover; land cover of interest > 70% at a grain

size of 500 m²). Tree types within the sample locations all consisted of deciduous trees. In each of these locations, *P. aegeria* females have been repeatedly observed since 2016 (S. Braem, A. Kaiser, C. Turlure and T. Merckx, personal observations). Urban sample locations were at two city parks (Aalst and Leuven), a cemetery (Brussels) and a small woodland patch near the city centre (Tienen). Agricultural locations consisted of small woodlots, hedgerows and sunken lanes along meadows and cultivated fields. Locations differed with an altitudinal range of 80 m at most (see description Fig. 1) and showed usually limited topographic variation within location (maximum altitude difference between two sample sites never exceeded 20m, except in the agricultural site in Leuven where the maximum difference was 42m).

205

206Climatic measures

Microclimatic measures were taken during a period of six weeks from the 13th of June until the 25th of July 2018. This period covers the start of summer conditions during which the species spends its life in large parts as egg or larva (i.e., in between two peaks of adult stages, which represent the first two annual generations) and may be particularly vulnerable to microclimatic conditions (Schweiger et al., 2006; Oliver et al., 2015; Pateman et al. 2016). Our Belgian study system experienced exceptionally warm and dry weather at that time (average temperature: 20.5°C during June & July 2018 vs. 17.3°C June & July 1830-2010; precipitation: 19 mm/m² vs. 100 mm/m² for the same 42-day period averaged for 1830 - 2010; Belgian Meteorological Institute KMI-RMI Brussels-Ukkel).

Within each location we measured temperature and relative humidity (RH) in two sample sites, using climatic sensors connected to a data logger (HOBO U23 v2; temperature accuracy of $\pm 0.2^{\circ}\text{C}$ from 0° to 50°C and a RH accuracy of $\pm 2.5\%$ from 10% to 90% and $\pm 5\%$ below

21910% and above 90%; Onset Computer Corporation, 2010). The sensors measured relative
220humidity and temperature every 30 minutes. Every week for six weeks, we randomized
221sample sites by moving the two HOBO sensors to a different sample site, positioning them
222within a 100m perimeter of the previous sampling site (see Fig. 1b-d as example).

223Although several herbivorous insects can be found on grasses, we selected a number of grassy
224microhabitats that corresponded to the oviposition site search profile of *Pararge aegeria* as an
225instructive case. During summer, females prefer tufts of grass in a humid and thermally
226buffered, semi-canopy-shaded microhabitat (Shreeve, 1986b, Schweiger et al., 2006; Oliver et
227al., 2015; Pateman et al. 2016). We positioned the microclimatic sensors at tufts of host grass
228at 12 cm above ground and in partial or nearly full shade of the surrounding canopy layer,
229which were always deciduous. We did not use any casing to shield off the HOBO climatic
230sensors to better simulate biologically realistic conditions and thus increase sensitivity to
231variation in wind and direct exposure to solar radiation (Terando et al., 2017). However, to
232avoid direct heating through the semi-transparent lid of the HOBO sensor, sensors were
233provided with a green plastic roof (\varnothing 90 mm), positioned at 15 mm above the sensor (see Fig.
2341e). Nine of the 144 data logger series were lost due to either issues with the HOBO climatic
235sensors or failure of data transfer from the logger.

236Degree of canopy openness was recorded for each sample site by taking a picture while
237poisoning the camera 12 cm above ground and facing a fisheye lens camera skywards with the
238horizontal part of the frame in an east-west orientation (full-frame Fisheye Converter FCON-
239T01 with a diagonal 130° angle of view; Olympus Tough TG-4 camera). Afterwards, we
240corrected for the southward position of the sun (at the highest point of the sun path, solar
241zenith angle ranged between 27° and 32°) by using only the 75% southside-segment of the
242picture. This procedure resulted in canopy segments with a zenithal angle of 41.8° and an
243azimuthal angle of 74.3° with the centre point 7.0° tilted to the south. We used ImageJ

244freeware (<https://imagej.nih.gov/ij/>) to transform pictures into black and white format and
245lowered brightness thresholds manually until mostly sky-obstructing vegetation was turned
246black and sky was turned white. Canopy openness was expressed as the percentage of white
247on the cropped pictures. Canopy openness was lacking for the three sample locations around
248Tienen.

249Hourly macroclimatic measures were recorded by The Royal Meteorological Institute of
250Belgium (KMI-RMI). Unfortunately, we only obtained measures over the course of a four
251week period and therefore had to deal with a lower sample size when testing for microclimatic
252differences (see below). We selected three of their nearby weather stations to retrieve these
253data: Bauvechevain (for all sites near Tienen and the forest site in Leuven), Melle (for all sites
254near Aalst), and Zaventem (for all sites near Brussels and the agricultural and urban site from
255Leuven; Fig. 1). All three weather stations were located in flat and open fields. At these
256stations, ambient temperature and relative humidity were measured 2 m above ground under
257standardized measuring conditions (i.e. casings with ‘Stevenson screens’ preventing the
258sensors from being directly exposed to sunlight or wind).

259

260Offset variables and microclimatic effects

261We obtained temperature and relative humidity (RH) data directly from HOBO climatic
262sensors and we derived Vapour Pressure Deficit (VPD) from the measurements of
263temperature and RH (Tetens 1930; Monteith & Unsworth 2013; for details on the calculation,
264see von Arx et al., 2013). To quantify the microclimatic conditions at the level of the host
265plant in different landscapes relative to the data from the weather stations (i.e. surrounding
266macroclimate), we used so-called offset microclimatic variables (De Frenne et al., 2019;
267Haesen et al., 2021). Microclimatic offset variables were calculated for each of the 135

268 weeklong sample series by subtracting average and standard deviation of local measures of
269 temperature, RH and VPD of a single weeklong sample series with the corresponding
270 averages and standard deviations from the nearby weather stations data. The selected nine
271 offset variables included offset day average (7:00 – 21:00 GMT+1), offset night average
272 (21:00 – 7:00 GMT+1) and offset standard deviation of T, RH and VPD. In all statistical
273 models, each of these calculated variables per sample series are treated as single replicates.
274 Correlation analysis showed a strong correlation between standard deviation and range (i.e.
275 maximum – minimum). However, standard deviation is less sensitive for short-lasting but
276 extreme measures.

277

278 **Other variables to tests for landscape type differences**

279 We used the microclimatic data to test for differences in microclimate relative to landscape
280 type. For each of the 135 weeklong time series, we used day mean, night mean, their standard
281 deviation, range, minimum and maximum value of temperature, RH and VPD. These 18
282 intercorrelated variables were standardized and integrated by a principal component analysis
283 (PCA) using R function ‘prcomp’ (R Core Team 2018).

284 Next, we introduced two variables reflecting the variability of VPD that aims to exclude
285 variation caused by repeated diurnal oscillations or by long-term trends over multiple days.
286 These variables were interpreted as negative correlates of predictability. For each of the
287 weeklong time series, short-term variability of VPD was calculated by taking the mean of the
288 residual variation (see ‘random’ in Appendix S1: Figure S1), after decomposition of time-
289 series-wide trends (see ‘trend’ in Appendix S1: Figure S1) and day-night variation (see
290 ‘cyclical’ in Appendix S1: Figure S1), using a decomposition algorithm that relies on moving
291 averages (i.e. ‘decompose’ function in R; Hyndman & Athanasopoulos, 2021). ‘Day-to-day

292 variability of VPD' represents how the standard deviation of VPD differs, on average, from
293 day to day and was calculated as follows: for one 7-day sequence of data, the difference in
294 standard deviation was calculated between measures of day 2 and day 3, day 3 and day 4, day
295 4 and day 5, and day 5 and day 6. Then, the average of those four values represented the 'day-
296 to-day variability'. Day 1 and day 7 were omitted from the calculation.

297

298 **Statistical modelling**

299 *Offset climatic variables to test for differences with weather station data for each landscape*
300 *type*

301 All statistics was performed using R 3.5.0 (R Core Team 2018). The effect of landscape type
302 on offset variables of T, RH and VPD was analysed with a linear mixed model with week as
303 random effect. Due to a limited amount of categories in our random factor (i.e. four weeks for
304 offset variables), we used Bayesian models using the brms package from R Studio (Bürkner,
305 2017). For every model, non-flat, weakly informative priors were specified (Appendix S1:
306 Section S3). 'Landscape type' and 'canopy openness' showed high collinearity as sites in
307 agricultural landscape were usually less enclosed by overhanging vegetation, while forest
308 sample sites had most overhanging vegetation (Appendix S1: Section S2, Fig. S2). Including
309 'canopy openness' as a categorical random variable (10 categories: 0-10%, 10-20%, ..., 90-
310 100%) resulted in very similar results as models without this random variable. Therefore, we
311 excluded 'canopy openness' as a fixed effect and tested each of our nine variables against
312 'canopy openness' as a fixed effect for each landscape in separate general linear models.

313 For the Bayesian model output (in R syntax: 'offset variable ~ landscape type + (1|week)') of
314 each of the nine microclimatic offset variables tested, we conducted two tests. First, we
315 derived the means of the microclimatic variables from the posterior samples for each

landscape type, and tested the deviance from zero with distribution boundaries calculated at a 95% credibility interval (CI). Second, we tested the difference of the microclimatic variables between landscape types. For this, we performed a non-linear hypothesis testing for each landscape type pair (agri vs. urban, agri vs. forest and urban vs. forest). We applied Bonferroni corrections to the threshold confidence interval.

Landscape differences in microclimate by PCA

Between-landscape differences were tested with the two first principal components that together explained 77% of the variation (PC1 explained 59 % and PC2 19%; Table 1) using a linear mixed model with week (N=6) as a random effect (Bates et al., 2015). In R syntax: 'PC1 or PC2 ~ landscape type + (1|week)'. A pairwise comparison was made among the least square means of the three landscape type, using linear contrasts. Bonferroni corrections were applied. We also present the results of the two variables that had the highest loadings in each of the two principal components, separately. These four variables, short-term variability of VPD and day-to-day variability of VPD were modelled similarly as PC1 and PC2.

RESULTS

Offset variables show landscape-related microclimatic differences

Output of the Bayesian mixed linear models are summarized in Fig. 2 and presented in Appendix S1: Table S2 ; between-landscape differences are presented in Appendix S1: Table S3. Offset RH was higher than zero in all three landscape types, indicating consistently more humid conditions near the grass layer. Humidity offset variables were highest during the day (day: 10-20% higher; night: 5-15% higher). Diurnal averages were highest in forest with an offset day RH +17.69% (95% CI: 14.29 – 20.83). Derived from the offset standard deviation, sample locations from agricultural settings showed higher temperature variability (i.e. +1.17

offset standard deviation of T; 95% CI: 0.48 – 1.77), but had equal variability for humidity. Urban and forest landscape settings showed lower variability in humidity compared to weather stations (urban: -1.81 offset standard deviation of RH; 95% CI: -3.21 - -0.46; forest: -3.62 offset standard deviation of RH; 95% CI: -4.01 - -1.23), but not in temperature and VPD. For offset day and offset night T, there was little deviation from zero, indicating that average temperature was similar to weather station data.

Agriculture settings scored highest in offset standard deviation (i.e. least climatically buffered) of temperature, RH and VPD compared to the other landscape types (Fig. 2). Offset day T was significantly higher when compared with the forest setting and offset day VPD was significantly higher than the other two landscape types (Fig 2). Offset night T was higher in urban than in forest sites (+0.85 offset day T; value tested against lies outside 98.3% interval).

351

Effect of canopy openness on microclimate depends on landscape type

Average canopy openness differed strongly between landscape types (mean canopy openness in agricultural settings \pm SE: $50 \pm 5\%$; urban settings: $37 \pm 5\%$; forest settings: $24 \pm 5\%$).

Once the dataset was subdivided in agricultural, urban and forest landscape types, distinct patterns on how canopy openness affects temperature and humidity offset variables became clear (Appendix S1: Table S1). For offset day T, RH and VPD in agricultural settings, we did not find an effect of canopy openness, whereas during the night offset T and offset VPD decreased and offset RH increased with canopy openness. In urban and forest settings, offset day T significantly increased with canopy openness while offset night T decreased with canopy openness. Offset night RH increases with canopy openness in urban (estimate = 0.18; $F_{1,22} = 10.43$, $p < 0.01$) and in agricultural settings (estimate back-transformed from a log-transformation = 0.13; $F_{1,21} = 0.39$, $p < 0.01$), while in forests there was no such an effect

(estimate = 0.039; $F_{1,20} = 0.39$, $p = 0.54$). In agricultural settings, offset standard deviation of T increased with canopy openness (estimate = 0.027; $F_{1,21} = 6.97$, $p < 0.05$). In urban settings, standard deviation of the three different offset variables was not affected by canopy openness. In forest settings, offset standard deviation of T and VPD increased with canopy openness (offset standard deviation of T: estimate = 0.023; $F_{1,20} = 13.654$, $p < 0.01$; offset standard deviation of VPD: estimate = 0.002; $F_{1,20} = 13.654$, $p < 0.01$).

370

Hotter and dryer conditions in agricultural settings, warmer nights in urban settings

A high PC1-score corresponded mainly with dry and hot day values and overall with more variable conditions (i.e., high standard deviation and range). A high PC2 corresponded with colder and more humid night conditions (see Table 1). For PC1, agricultural settings had significantly higher values compared to forest settings, while for PC2, agricultural settings had significantly higher values compared to both urban and forest settings, indicating colder and more humid nights (Fig. 3 and Appendix S1: Table S4).

The two highest contributing variables for PC1 were VPD standard deviation and day VPD. These showed similar trends as their corresponding offset variables in Figure 2, with higher day VPD and higher VPD fluctuations in agricultural settings compared to the other landscape types (Table 2). The two highest contributing variables for PC2 were night temperature and minimum temperature. On average, we observed 0.7°C higher night temperature in urban settings compared to the other two landscape types and 1.2°C higher minimum temperature in urban settings when compared to forests.

Our novel variables of VPD variability as a proxy measure of temporal predictability of microclimate had similar effects standard deviation of VPD: agricultural settings showed

387stronger day-to-day and short-term variability compared to forest settings. Short-term VPD
388variability in agricultural settings was also higher than in urban settings (Table 2).

389

390DISCUSSION

391Our study tested for differences in microclimatic profiles at the level of tufts of host grass that
392grow in woodland, agricultural land and urban environments, respectively. The study of
393microclimates has recently regained growing interest in the context of biodiversity responses
394to ongoing climate change (De Frenne et al. 2021), which is particularly significant for insects
395(Ma et al. 2021). There is a large community of grass-feeding insects, which interact on this
396small scale with their (thermal) environment. These insects include habitat generalists that can
397make use of similar grasses that occur in different structural habitat types (e.g. *Popillia*
398*japonica*; Lemoine et al. 2013), but also forest specialists that have recently expanded their
399habitat and host plant use beyond forest (e.g. *P. aegeria*; Vandewoestijne & Van Dyck 2010).
400Our results confirm that there is a significant difference between weather station data and
401microclimatic data measured at the level of the grasses, but here we show that such
402differences vary among landscape types. Microclimates at the level of the grass layer were
403better buffered under forest conditions than under non-forest conditions in anthropogenic
404landscapes. However, some of the microclimatic variables under urban conditions showed
405more resemblance to forest conditions than to the other non-forest landscape type, i.e.
406agricultural landscape. This clear difference between the two non-forest landscape categories
407opens new avenues for exploring microclimatic opportunities and undervalued resources of
408grass-feeding insects in anthropogenic landscapes.

409

410**Microclimate measures of grass habitat nearby trees deviates from weather station data**

411The ecological relevance of using readily available weather station data to interpret species-
412environment interactions at the microclimatic level has been criticized lately (Haesen et al.,
4132021; Lembrechts & Nijs, 2020). Our case study analysed this issue for microclimates around
414tufts of grass growing in different landscape settings, i.e. in forest, agricultural and urban
415landscape. Our study demonstrated that weather station measures taken with shielded sensors
4162 m above ground in open field do not correspond well with the habitat-specific microclimatic
417conditions at the level of the grass layer. Consequently, we endorse the plea for a more
418biologically realistic positioning of climatic sensors when studying organismal responses to
419climate (Ashcroft, 2018; Suggitt et al., 2011).

420As predicted, microclimatic conditions deviated significantly from time-matched measures of
421nearby weather station, particularly in terms of higher relative humidity and the related VPD.
422This is in accordance with well-established work on near-ground microclimate (Geiger et al.,
4232003) showing that RH can increase with 10% or more at ground surface, when compared to
4242 m above ground. In contrast with the overall opposite trends at bare ground, increasing
425humidity closer to the ground is only observed under the presence of vegetation layers such as
426grasses (Geiger et al., 2003). Surrounding tree canopy and understorey vegetation at each
427sample site likely contributed as well to higher humidity and buffering of humidity levels in
428comparison with open field conditions (De Frenne et al., 2013; Geiger et al., 2003). Overall,
429offset values showed that average day and night temperatures at the height of the grass
430corresponded well with those measured 2 m above ground and behind Stevenson
431screens. This effect was opposite to what one would expect from near-ground microclimates
432in dense grass vegetation (and other vegetation near ground), which ensures better thermal
433buffering: surface layers receive less direct solar radiation during the day and receive
434relatively higher infrared ground radiation during the night (Geiger et al., 2003; Morecroft et
435al., 1998; von Arx et al., 2013). However, other mechanisms may counter this higher-

436buffering-near-ground effect. For example, in an open field with little ground vegetation,
437thermal buffering capacity at 12 cm above ground is generally lower than that at 2 m height.
438This is caused by the relatively cooler ground surface at night due to convective cooling, and
439a relatively decreased surface cooling during the day due to wind-generated boundary layer
440effects (wind speed is usually lower during the night; Geiger et al., 2003; Munro, 1987). This
441also confirms why we only found higher thermal variability near-ground-offset values in
442agricultural but not in forest and urban landscape types. (Geiger et al., 2003; Morecroft et al.,
4431998; von Arx et al., 2013).

444

445**Microclimate of grass habitat nearby trees is affected by landscape**

446In agricultural landscapes, offset variables of standard deviation of temperature, day-to-day
447variability in VPD and short-term variability in VPD all showed higher values, when
448compared to urban and forest conditions. Therefore, as predicted, agricultural settings were
449characterized by stronger fluctuations in both temperature and humidity. Agricultural sites
450were more exposed to sun radiation, drought and heat, which creates harsher microclimates
451for drought-sensitive insects. Nevertheless, variation of canopy openness did not exert
452microclimatic changes in day temperature for grasses on agricultural sites, while there was a
453positive effect for grasses in the other two landscape types. Small-scale effects by wind and
454soil humidity, which were not measured in our current study, may also contribute to the
455observed microclimate effects. During summers in the temperate-zone region, urban areas
456typically have drier soils and lower wind speeds (Larsen, 2015), open fields have drier soils
457and stronger winds (von Arx et al., 2013) and forests wetter soils and lower wind speeds
458(Boggs & McNulty, 2010; Morecroft et al., 1998; von Arx et al., 2013). Hence, woodlots in
459agricultural sites are likely to experience more wind, partly dampening solar heating at solar-

460exposed sample sites, making these microsites in a way more similar to canopy-shaded
461microsites.

462Forest conditions provided higher buffering capacity in grassy sites for both temperature and
463humidity. However, lower canopy openness is not likely to be the only mechanism, as our
464results showed that contributing effects of canopy openness were relatively low; the effects
465may interact with other factors such as soil moisture and wind speed (Boggs & McNulty,
4662010; von Arx et al., 2013). Assuming higher soil humidity, as typically observed for forest
467soils, our results on RH and VPD are in agreement with those of von Arx et al. (2013): wet
468soils maintain high above ground humidity levels, which will dampen the effects of canopy
469cover on near-ground VPD. The humidity effect of canopy cover was much more pronounced
470for grasses growing in urban and agricultural sites (i.e., on relatively drier soils). For
471temperature, the forest canopy effect was more pronounced (Appendix S1: Table S1).
472However, we need to be cautious with this comparison, as von Arx et al. (2013) retrieved data
473measured at 2 m above surface. Higher above surface heat is disseminated more strongly than
474air moisture (Geiger et al., 2003), which may explain why canopy cover and soil moisture
475interact with temperature in a different way at different heights above ground.

476A second reason why landscape effects may overshadow local effects (e.g., canopy cover)
477relates to the higher-order thermodynamic effects of large forests. Large forests become more
478thermodynamically stable in terms of evapotranspiration and temperature with increasing
479vegetation abundance per surface unit (Whittaker, 1975; H. Zhang & Wu, 2002). Increased
480vegetation complexity increases the capacity to capture and dissipate solar energy, making
481landscapes where such vegetation is dominant, more resilient to deal with external fluxes,
482which can be detected at both the macro- (Ehbrecht et al., 2021; Norris et al., 2011; Schneider
483& Kay, 1994) and micro-climatic level (Redmond et al., 2018; von Arx et al., 2013).

484 We detected Urban Heat Island effects as night temperature was on average 0.7°C higher
485 around grass tufts in urban sites than around grasses in agricultural and forest sites. These
486 urban heat effects were expected to be mild for two reasons. First, built-up surface areas of
487 most urban areas were relatively small. Larger cities, such as Birmingham (229.8 km²),
488 generated 0.7°C to 3.4°C higher night temperatures during the summer (Azevedo et al., 2016).
489 Hence, the increase we observed was at the lower end of this range. Second, woody and
490 grassy vegetation that surrounded a tuft of grass will help dampen local Urban Heat Island
491 effects, especially during the day (Yan, 2019; Y. Zhang, 2017). This has also been argued by
492 Kaiser et al. (2016), showing 1°C higher average day temperature – but not night temperature
493 – in urban sites compared to agricultural sites. Kaiser et al. (2016) analysed the effect of
494 urbanisation on larval microclimate in *P. aegeria* and took measurements at 1 m height in late
495 summer to early spring. Although such an experimental set-up does not allow direct
496 comparison with our findings, it does stress the importance of season- and height-dependent
497 microclimatic conditions within a species' functional habitat (Ashcroft, 2018; Suggitt et al.,
498 2011; Vermunt et al., 2012). As predicted, relatively higher night temperatures, but not higher
499 day temperatures, contributed to higher microclimatic buffering capacity in urban sites
500 compared to agricultural sites.

501

502 **Microclimatic properties of host grasses out of forest: an insect's viewpoint**

503 *Egg and larval development*

504 The landscape-specific effects on local microclimates around grass tufts provide insight on
505 how grass-feeding insects are exposed to different microclimatic conditions. To the butterfly
506 *P. aegeria*, which expanded its habitat use from forest to agricultural and urban environments
507 over the last decades, agricultural microclimates pose a significant challenge for early
508 development. Later larval stages are, to some extent, able to tolerate a larger thermal range as

they are able to move to the cooler and more humid centre of the grass sward under high temperatures (Berger et al., 2011; Kaiser et al., 2016). For example, Kaiser et al. (2016) found no differences in larval survival when – from second instar onwards – being exposed to dryer environments or when comparing agricultural vs. woodland ecotypes (however, their experiment was not performed during periods of extended drought and heat, thereby mitigating the risks of desiccation in more exposed environments). In contrast, the egg and first instar stages are more likely to be affected by heat stress, as has been shown in several satyrine butterfly species and other Lepidoptera (Bergman, 1999; Clark & Faeth, 1998; Karlsson & Wiklund, 1985; Klockmann et al., 2017; Potter et al., 2011; Zhang et al., 2015). At 30% relative humidity and 20°C (VPD: 1.63 kPa), Karlsson & Wiklund (1985) showed *P. aegeria* egg survival to be at 29% only. 3% of our obtained values for mean day VPD exceeded 1.63 kPa in forest, 10% in urban areas and 23% in agricultural areas (Appendix S1: Fig. S3). Hence, during hot summers, our measurements suggest that oviposition sites with low risk of desiccation are less frequently available in agricultural landscape settings. Urban habitats could provide microclimatic conditions for eggs and larvae that are far more similar to those found in forest habitat. Additionally, higher urban night temperatures may benefit larval development as it increases foraging rate overnight and induces overall faster larval growth (Berger et al., 2011; Chown & Nicolson, 2004). So, at the smaller spatial scale, immobile egg stages may benefit from microhabitats that are sufficiently hygrothermally buffered against climatic extremes (e.g., semi-shaded conditions in the grass, 12 cm above ground and near larger, dense vegetation). However, at the larger spatial scale of a few meters, more mobile and larger life stages may benefit from both patches of elevated solar radiation used for basking and patches that are more buffered against climatic extremes (Anthes et al., 2008; Woods, 2013; Pincebourde et al. 2021). This shows that microclimatic mosaics at various spatial scales – from egg microhabitats to the structural habitat in a

landscape – need to be taken into account when studying how microclimate affects an insect's survival in times of climatic change.

Microclimate and environmental predictability

Short-term and day-to-day variability in VPD reflect variation in desiccation risks over the span of hours or days, respectively. These values were again higher in grasses in agricultural landscape, where surrounding vegetation was lower and wind exposure higher. On the short-term, a canopy-open spot is more exposed to the fluctuating conditions of cloudiness that may or may not let sunbeams pass, but a spot that is covered by canopy is never exposed whether sunny or not. On a day-to-day resolution, uncertainties about the microclimate may impose constraints on larval foraging behaviour (e.g., decisions to move to the base of the plant, or to increase foraging). These levels of environmental predictability at different temporal resolutions open new perspectives for studies on how organisms deal with life-history strategies, ranging from (ir)reversible plasticity, learning to bet hedging (Botero et al., 2015; Joschinski & Bonte, 2020). In sticklebacks, for example, higher thermal uncertainty on a week-to-week temporal resolution has been shown to induce bet-hedging strategies for egg size (Shama, 2015).

Microhabitat and adult behaviour

The spatial patterns of the microclimatic variations are experienced differently for flying adults – where microclimates significantly fluctuate both horizontally (Montejo-Kovacevich et al., 2020) and vertically (Pryke et al., 2012) – when compared to mobile larvae and even more when compared to the eggs or the little mobile first instar larvae. Our results imply that oviposition sites with a hydrothermally buffered microclimate are differently distributed and possibly harder to find in microhabitats in agricultural landscape than in urban and forest landscapes. Such differences in spatial configuration are likely to have fitness consequences

for searching females that need to balance energetic costs with microclimatic preferences during oviposition (García-Barros & Fartmann, 2009; Resetarits, 1996; Shreeve, 1986b). Microclimatic preference and site selection strategies are therefore expected to differ relative to the type of environment. For example, Braem et al. (2021) showed that ovipositing butterflies of agricultural landscape origin were more willing to accept locally available oviposition sites than butterflies of forest origin, even when microclimatic conditions were not optimal. In a common garden laboratory experiment, females of the agricultural ecotype laid more and heavier eggs under high ambient temperatures compared to conspecific females of the forest ecotype (Karlsson & Van Dyck, 2005). Therefore, mapping the spatial configuration of microclimates could benefit future research on movement and reproductive ecology of small ectotherm organisms, especially those that colonize areas undergoing rapid environmental change (Fagan et al., 2013).

In conclusion, we showed that agricultural, but not urban, habitat settings reduced the microclimatic buffering of host plants in space and time, when compared to microhabitat settings in forest landscapes. We emphasize the possible implications of these differences for grass feeding butterflies and insects occupying similar niches, in particular during immobile stages of higher hydrothermal sensitivity and during extreme weather conditions. Although this study was initially inspired by the specific resource-based habitat point of view of the larval stages of *P. aegeria*, the significance of our results is much broader as they allow to better understand how microclimatic conditions around and on grasses are shaped in different anthropogenic environments.

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587

588**AUTHOR CONTRIBUTIONS**

589S.B., C.N. and H.V.D. co-designed the study and prepared the experiment. S.B. collected and
590analyzed the data in interaction with M.C, C.N. and H.V.D. S.B. and H.V.D. wrote the first
591draft of the paper. All authors discussed the results and contributed critically to the final
592manuscript. All authors gave final approval for publication.

593

594**CONFLICT OF INTEREST STATEMENT**

595The authors have no relevant financial or non-financial interests to disclose.

596 REFERENCES

- 597 Aguirre, B. A., Hsieh, B., Watson, S. J., & Wright, A. J. (2021). The experimental
598 manipulation of atmospheric drought: Teasing out the role of microclimate in biodiversity
599 experiments. *Journal of Ecology*, 109(5), 1986–1999. <https://doi.org/10.1111/1365-2745.13595>
- 600 Anthes, N., Fartmann, T., & Hermann, G. (2008). The Duke of Burgundy butterfly and its
601 dukedom: Larval niche variation in *Hamearis lucina* across Central Europe. *Journal of Insect*
602 *Conservation*, 12(1), 3–14. <https://doi.org/10.1007/s10841-007-9084-7>
- 603 Arnfield, A. J. (2003). Two decades of urban climate research: A review of turbulence,
604 exchanges of energy and water, and the urban heat island. *International Journal of*
605 *Climatology*, 23(1), 1–26. <https://doi.org/10.1002/joc.859>
- 606 Ashcroft, M. B. (2018). Which is more biased: Standardized weather stations or microclimatic
607 sensors? *Ecology and Evolution*, 8(11), 5231–5232. <https://doi.org/10.1002/ece3.3965>
- 608 Azevedo, J., Chapman, L., & Muller, C. (2016). Quantifying the Daytime and Night-Time
609 Urban Heat Island in Birmingham, UK: A Comparison of Satellite Derived Land Surface
610 Temperature and High Resolution Air Temperature Observations. *Remote Sensing*, 8(2), 153.
611 <https://doi.org/10.3390/rs8020153>
- 612 Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models
613 Using lme4. *Journal of Statistical Software*, 67(1), 1–48. <https://doi.org/10.18637/jss.v067.i01>
- 614 Bauerfeind, S. S., & Fischer, K. (2013). Increased temperature reduces herbivore host-plant
615 quality. *Global Change Biology*, n/a-n/a. <https://doi.org/10.1111/gcb.12297>
- 616 Berger, D., Friberg, M., & Gotthard, K. (2011). Divergence and ontogenetic coupling of
617 larval behaviour and thermal reaction norms in three closely related butterflies. *Proceedings*

618of the Royal Society B: Biological Sciences, 278(1703), 313–320.

619<https://doi.org/10.1098/rspb.2010.1398>

620Bergman, K.-O. (1999). Habitat utilization by *Lopinga achine* (Nymphalidae: Satyrinae)

621larvae and ovipositing females: implications for conservation. *Biological Conservation*, 88(1),

62269–74. [https://doi.org/10.1016/S0006-3207\(98\)00088-3](https://doi.org/10.1016/S0006-3207(98)00088-3)

623Boggs, J. L., & McNulty, S. G. (2010). Changes in canopy cover alter surface air and forest

624floor temperature in a high-elevation red spruce (*Picea rubens* Sarg.) forest. In J. S. Rentch &

625T. M. Schuler (Eds.), *Proceedings from the conference on the ecology and management of*

626*high-elevation forests in the central and southern Appalachian Mountains* (pp. 13–21).

627Newtown Square, PA: Department of Agriculture, Forest Service, Northern Research Station.

628Botero, C. A., Weissing, F. J., Wright, J., & Rubenstein, D. R. (2015). Evolutionary tipping

629points in the capacity to adapt to environmental change. *Proceedings of the National*

630*Academy of Sciences*, 112(1), 184–189. <https://doi.org/10.1073/pnas.1408589111>

631Braem, S., Turlure, C., Nieberding, C., & Van Dyck, H. (2021). Oviposition site selection and

632learning in a butterfly under niche expansion: An experimental test. *Animal Behaviour*, 180,

633101–110. <https://doi.org/10.1016/j.anbehav.2021.08.011>

634Bürkner, P. (2017). brms: An R Package for Bayesian Multilevel Models Using Stan. *Journal*

635*of Statistical Software*, 80(1), 1–28. <https://doi.org/10.18637/jss.v080.i01>

636Chick, L. D., Waters, J. S., & Diamond, S. E. (2021). Pedal to the metal: Cities power

637evolutionary divergence by accelerating metabolic rate and locomotor performance.

638*Evolutionary Applications*, 14(1), 36–52. <https://doi.org/10.1111/eva.13083>

639Chown, S., & Nicolson, S. W. (2004). *Insect physiological ecology: Mechanisms and*

640*patterns*. Oxford, UK: Oxford University Press.

641Clark, B. R., & Faeth, S. H. (1998). The evolution of egg clustering in butterflies: A test of
642the egg desiccation hypothesis. *Evolutionary Ecology*, 12(5), 543–552.
643<https://doi.org/10.1023/A:1006504725592>

644Davies-Colley, R. J., Payne, G. W., & van Elswijk, M. (2000). Microclimate gradients across
645a forest edge. *New Zealand Journal of Ecology*, 24(2), 111–121.
646<http://www.jstor.org/stable/24054666>

647De Frenne, P., Rodriguez-Sanchez, F., Coomes, D. A., Baeten, L., Verstraeten, G., Vellend,
648M., Bernhardt-Romermann, M., Brown, C. D., Brunet, J., Cornelis, J., Decocq, G. M.,
649Dierschke, H., Eriksson, O., Gilliam, F. S., Hedl, R., Heinken, T., Hermy, M., Hommel, P.,
650Jenkins, M. A., ... Verheyen, K. (2013). Microclimate moderates plant responses to
651macroclimate warming. *Proceedings of the National Academy of Sciences*, 110(46), 18561–
65218565. <https://doi.org/10.1073/pnas.1311190110>

653De Frenne, P., Zellweger, F., Rodríguez-Sánchez, F., Scheffers, B. R., Hylander, K., Luoto,
654M., Vellend, M., Verheyen, K., & Lenoir, J. (2019). Global buffering of temperatures under
655forest canopies. *Nature Ecology & Evolution*, 3(5), 744–749. [https://doi.org/10.1038/s41559-](https://doi.org/10.1038/s41559-019-0842-1)
656019-0842-1

657De Frenne, P., Lenoir, J., Luoto, M., Scheffers, B. R., Zellweger, F., Aalto, J., Ashcroft, M.
658B., Christiansen, D. M., Decocq, G., De Pauw, K., Govaert, S., Greiser, C., Gril, E., Hampe,
659A., Jucker, T., Klimes, D.H., Koelemeijer, I. A., Lembrechts, J. J., Marrec, R., Meeussen, C.,
660Ogée, J., Tyystjärvi, V., Vangansbeke, P., & Hylander, K.. (2021). Forest Microclimates and
661Climate Change: Importance, Drivers and Future Research Agenda. *Global Change Biology*,
66227(11):2279–97. doi: 10.1111/gcb.15569.

663Dennis, R., Shreeve, T., & Van Dyck, H. (2003). Towards a Functional Resource-Based
 664Concept for Habitat: A Butterfly Biology Viewpoint. *Oikos*, 102(2):417–426. doi:
 66510.1034/j.1600-0579.2003.12492.x.

666Dillon, M. E., Woods, H. A., Wang, G., Fey, S. B., Vasseur, D. A., Telemeco, R. S., Marshall,
 667K., & Pincebourde, S. (2016). Life in the Frequency Domain: The Biological Impacts of
 668Changes in Climate Variability at Multiple Time Scales. *Integrative and Comparative*
 669*Biology*, 56(1), 14–30. <https://doi.org/10.1093/icb/icw024>

670Doody, J. S., Guarino, E., Georges, A., Corey, B., Murray, G., & Ewert, M. (2006). Nest site
 671choice compensates for climate effects on sex ratios in a lizard with environmental sex
 672determination. *Evolutionary Ecology*, 20(4), 307–330. <https://doi.org/10.1007/s10682-006->
 6730003-2

674Ehbrecht, M., Seidel, D., Annighöfer, P., Kreft, H., Köhler, M., Zemp, D. C., Puettmann, K.,
 675Nilus, R., Babweteera, F., Willim, K., Stiers, M., Soto, D., Boehmer, H. J., Fisichelli, N.,
 676Burnett, M., Juday, G., Stephens, S. L., & Ammer, C. (2021). Global patterns and climatic
 677controls of forest structural complexity. *Nature Communications*, 12(1), 519.
 678<https://doi.org/10.1038/s41467-020-20767-z>

679Ewers, R. M., & Banks-Leite, C. (2013). Fragmentation Impairs the Microclimate Buffering
 680Effect of Tropical Forests. *PLoS ONE*, 8(3), e58093.
 681<https://doi.org/10.1371/journal.pone.0058093>

682Evans, K. L., Gaston, K. J., Frantz, A. C., Simeoni, M., Sharp, S. P., McGowan, A., Dawson,
 683D. A., Walasz, K., Partecke, J., Burke, T., & Hatchwell, B. J. (2009). Independent
 684Colonization of Multiple Urban Centres by a Formerly Forest Specialist Bird Species.
 685*Proceedings of the Royal Society B: Biological Sciences*, 276(1666):2403–2410. doi: 10.1098/
 686rspb.2008.1712.

687Fagan, W. F., Lewis, M. A., Auger-Méthé, M., Avgar, T., Benhamou, S., Breed, G., LaDage,
688L., Schlägel, U. E., Tang, W., Papastamatiou, Y. P., Forester, J., & Mueller, T. (2013). Spatial
689memory and animal movement. *Ecology Letters*, 16(10), 1316–1329. [https://doi.org/10.1111/](https://doi.org/10.1111/ele.12165)
690ele.12165

691García-Barros, E., & Fartmann, T. (2009). Butterfly oviposition: Sites, behaviour and modes.
692In J. Settele, T. Shreeve, M. Konvička, & H. Van Dyck (Eds.), *Ecology of Butterflies in*
693*Europe* (pp. 29–42). Cambridge, MA: Cambridge University Press.

694Geiger, R., Aron, R. H., & Todhunter, P. (2003). *The Climate Near the Ground* (6th ed.).
695Rowman & Littlefield. <https://doi.org/10.1007/978-3-322-86582-3>

696Haesen, S., Lembrechts, J. J., Frenne, P. D., Lenoir, J., Aalto, J., Ashcroft, M. B., Kopecký,
697M., Luoto, M., Maclean, I., Nijs, I., Niittynen, P., Arriga, N., Bruna, J., Buchmann, N., Čiliak,
698M., Collalti, A., Lombaerde, E. D., Descombes, P., Gharun, M., ... Meerbeek, K. V. (2021).
699ForestTemp – Sub-canopy microclimate temperatures of European forests. *Global Change*
700*Biology*, 13. <https://doi.org/10.1111/gcb.15892>

701Hyndman, R. J., & Athanasopoulos, G. (2021). *Forecasting: Principles and practice* (3rd ed.)
702Melbourne, Australia: OTexts.

703Jang, T., Rho, M. S., Koh, S.-H., & Lee, K. P. (2015). Host-plant quality alters herbivore
704responses to temperature: A case study using the generalist *Hyphantria cunea*. *Entomologia*
705*Experimentalis et Applicata*, 154(2), 120–130. <https://doi.org/10.1111/eea.12261>

706Joschinski, J., & Bonte, D. (2020). Transgenerational Plasticity and Bet-Hedging: A
707Framework for Reaction Norm Evolution. *Frontiers in Ecology and Evolution*, 8, 517183.
708<https://doi.org/10.3389/fevo.2020.517183>

709Kaiser, A., Merckx, T., & Van Dyck, H. (2016). The Urban Heat Island and its spatial scale
710dependent impact on survival and development in butterflies of different thermal sensitivity.
711*Ecology and Evolution*, 6(12), 4129–4140. <https://doi.org/10.1002/ece3.2166>

712Karlsson, B., & Van Dyck, H. (2005). Does habitat fragmentation affect temperature-related
713life-history traits? A laboratory test with a woodland butterfly. *Proceedings of the Royal*
714*Society B: Biological Sciences*, 272(1569), 1257–1263.
715<https://doi.org/10.1098/rspb.2005.3074>

716Karlsson, B., & Wiklund, C. (1985). Egg weight variation in relation to egg mortality and
717starvation endurance of newly hatched larvae in some satyrid butterflies. *Ecological*
718*Entomology*, 10(2), 205–211. <https://doi.org/10.1111/j.1365-2311.1985.tb00549.x>

719Klockmann, M., Kleinschmidt, F., & Fischer, K. (2017). Carried over: Heat stress in the egg
720stage reduces subsequent performance in a butterfly. *PLOS ONE*, 12(7), e0180968.
721<https://doi.org/10.1371/journal.pone.0180968>

722Larsen, L. (2015). Urban climate and adaptation strategies. *Frontiers in Ecology and the*
723*Environment*, 13(9), 486–492. <https://doi.org/10.1890/150103>

724Lembrechts, J. J., & Nijs, I. (2020). Microclimate shifts in a dynamic world. *Science*,
725368(6492), 711–712. <https://doi.org/10.1126/science.abc1245>

726Lemoine, N. P., Drews, W. A., Burkepille, D. E., & Parker J. D. 2013. Increased Temperature
727Alters Feeding Behavior of a Generalist Herbivore. *Oikos*, 122(12):1669–78. doi:
72810.1111/j.1600-0706.2013.00457.x.

729Lin, H., Tu, C., Fang, J., Gioli, B., Loubet, B., Gruening, C., Zhou, G., Beringer, J., Huang, J.,
730Dušek, J., Liddell, M., Buysse, P., Shi, P., Song, Q., Han, S., Magliulo, V., Li, Y., & Grace, J.

731(2020). Forests buffer thermal fluctuation better than non-forests. *Agricultural and Forest*
732*Meteorology*, 288–289, 107994. <https://doi.org/10.1016/j.agrformet.2020.107994>

733Lowe, E. C., Wilder, S. M., & Hochuli, D. F. (2014). Urbanisation at Multiple Scales Is
734Associated with Larger Size and Higher Fecundity of an Orb-Weaving Spider. *PLoS ONE*,
7359(8), e105480. <https://doi.org/10.1371/journal.pone.0105480>

736Ma, C., Ma, G., & Pincebourde. (2021). Survive a Warming Climate: Insect Responses to
737Extreme High Temperatures. *Annual Review of Entomology*, 66(1):163–84. doi:
73810.1146/annurev-ento-041520-074454.

739Massmann, A., Gentine, P., & Lin, C. (2019). When Does Vapor Pressure Deficit Drive or
740Reduce Evapotranspiration? *Journal of Advances in Modeling Earth Systems*, 11(10), 3305–
7413320. <https://doi.org/10.1029/2019MS001790>

742Merckx, T., Souffreau, C., Kaiser, A., Baardsen, L. F., Backeljau, T., Bonte, D., Brans, K. I.,
743Cours, M., Dahirel, M., Debortoli, N., De Wolf, K., Engelen, J. M. T., Fontaneto, D.,
744Gianuca, A. T., Govaert, L., Hendrickx, F., Higuti, J., Lens, L., Martens, K., ... Van Dyck, H.
745(2018). Body-size shifts in aquatic and terrestrial urban communities. *Nature*, 558(7708),
746113–116. <https://doi.org/10.1038/s41586-018-0140-0>

747Middel, A., Chhetri, N., & Quay, R. (2015). Urban forestry and cool roofs: Assessment of
748heat mitigation strategies in Phoenix residential neighborhoods. *Urban Forestry & Urban*
749*Greening*, 14(1), 178–186. <https://doi.org/10.1016/j.ufug.2014.09.010>

750Monteith, J. L., & Unsworth, M. (2013). Principles of environmental physics: Plants, animals,
751and the atmosphere (4th ed). Boston, MA: Elsevier.

752Montejo-Kovacevich, G., Martin, S. H., Meier, J. I., Bacquet, C. N., Monllor, M., Jiggins, C.
753D., & Nadeau, N. J. (2020). Microclimate buffering and thermal tolerance across elevations in

754a tropical butterfly. *The Journal of Experimental Biology*, 223(8), jeb220426.

755<https://doi.org/10.1242/jeb.220426>

756Morecroft, M. D., Taylor, M. E., & Oliver, H. R. (1998). Air and soil microclimates of
757deciduous woodland compared to an open site. *Agricultural and Forest Meteorology*, 90(1–
7582), 141–156. [https://doi.org/10.1016/S0168-1923\(97\)00070-1](https://doi.org/10.1016/S0168-1923(97)00070-1)

759Munro, D. (1987). Boundary layer climatology. In J. Oliver & R. Fairbridge (Eds.),
760*Climatology. Encyclopedia of Earth Science*. (pp. 172–183). Springer US.

761https://doi.org/10.1007/0-387-30749-4_29

762Murdock, C. C., Evans, M. V., McClanahan, T. D., Miazgowicz, K. L., & Tesla, B. (2017).
763Fine-scale variation in microclimate across an urban landscape shapes variation in mosquito
764population dynamics and the potential of *Aedes albopictus* to transmit arboviral disease.
765*PLOS Neglected Tropical Diseases*, 11(5), e0005640.

766<https://doi.org/10.1371/journal.pntd.0005640>

767Norris, C., Hobson, P., & Ibisch, P. L. (2011). Microclimate and vegetation function as
768indicators of forest thermodynamic efficiency: Forest thermodynamic efficiency. *Journal of*
769*Applied Ecology*, 49, 562–570. <https://doi.org/10.1111/j.1365-2664.2011.02084.x>

770Oliver, T. H., Marshall, H. H., Morecroft, M. D., Brereton, T., Prudhomme, C., &
771Huntingford, C. (2015). Interacting effects of climate change and habitat fragmentation on
772drought-sensitive butterflies. *Nature Climate Change*, 5(10), 941–945.

773<https://doi.org/10.1038/nclimate2746>

774Parmentier, T., Vanderheyden, A., Dekoninck, W., & Wenseleers, T. (2017). Body size in the
775ant-associated isopod *Platyarthrus hoffmannseggii* is host-dependent. *Biological Journal of*
776the Linnean Society, 121(2), 305–311. <https://doi.org/10.1093/biolinnean/blw052>

777 Pateman, R. M., Thomas, C. D., Hayward, S. A. L., & Hill, J. K. (2016). Macro- and
 778 microclimatic interactions can drive variation in species' habitat associations. *Global Change*
 779 *Biology*, 22(2), 556–566. <https://doi.org/10.1111/gcb.13056>
 780 Pincebourde, S., Murdock, C. C.,
 781 Vickers, M., & Sears, M. W. (2016). Fine-Scale Microclimatic Variation Can Shape the
 782 Responses of Organisms to Global Change in Both Natural and Urban Environments.
 783 *Integrative and Comparative Biology*, 56(1), 45–61. <https://doi.org/10.1093/icb/icw016>
 784 Pincebourde, S., & Woods, H. A. (2012). Climate uncertainty on leaf surfaces: The
 785 biophysics of leaf microclimates and their consequences for leaf-dwelling organisms.
 786 *Functional Ecology*, 26(4), 844–853. <https://doi.org/10.1111/j.1365-2435.2012.02013.x>
 787 Pincebourde, S., & Woods, H. A. (2020). There is plenty of room at the bottom:
 788 Microclimates drive insect vulnerability to climate change. *Current Opinion in Insect Science*,
 789 41, 63–70. <https://doi.org/10.1016/j.cois.2020.07.001>
 790 Pincebourde, S., Dillon, M. E., & Woods, H. A. (2021). Body size determines the thermal
 791 coupling between insects and plant surfaces. *Functional Ecology*, 35(7), 1424–1436.
 792 <https://doi.org/10.1111/1365-2435.13801>
 793 Potter, K. A., Davidowitz, G., & Arthur Woods, H. (2011). Cross-stage consequences of egg
 794 temperature in the insect *Manduca sexta*: Cross-stage effects of egg temperature. *Functional*
 795 *Ecology*, 25(3), 548–556. <https://doi.org/10.1111/j.1365-2435.2010.01807.x>
 796 Pryke, J. S., Vrdoljak, S. M., Grant, P. B. C., & Samways, M. J. (2012). Butterfly behavioural
 797 responses to natural Bornean tropical rain-forest canopy gaps. *Journal of Tropical Ecology*,
 798 28(1), 45–54. <https://doi.org/10.1017/S0266467411000502>

799Redmond, M. D., Weisberg, P. J., Cobb, N. S., & Clifford, M. J. (2018). Woodland resilience
800to regional drought: Dominant controls on tree regeneration following overstorey mortality.
801*Journal of Ecology*, 106(2), 625–639. <https://doi.org/10.1111/1365-2745.12880>

802Resetarits, W. J. (1996). Oviposition Site Choice and Life History Evolution. *American*
803*Zoologist*, 36(2), 205–215. <https://doi.org/10.1093/icb/36.2.205>

804Rickards, K., & Boulding, E. (2015). Effects of temperature and humidity on activity and
805microhabitat selection by *Littorina subrotundata*. *Marine Ecology Progress Series*, 537, 163–
806173. <https://doi.org/10.3354/meps11427>

807Righi, C. A., Sandoval Rodríguez, C., Ferreira, E. N. L., Godoy, W. A. C., & Cognato, A. I.
808(2018). Microclimatic Conditions for Dung Beetle (Coleoptera: Scarabaeidae) Occurrence:
809Land Use System as a Determining Factor. *Environmental Entomology*, 47(6), 1420–1430.
810<https://doi.org/10.1093/ee/nvy163>

811Schneider, E. D., & Kay, J. J. (1994). Complexity and thermodynamics. *Futures*, 26(6), 626–
812647. [https://doi.org/10.1016/0016-3287\(94\)90034-5](https://doi.org/10.1016/0016-3287(94)90034-5)

813Schweiger, O., Dormann, C. F., Bailey, D., & Frenzel, M. (2006). Occurrence pattern of
814*Pararge aegeria* (Lepidoptera: Nymphalidae) with respect to local habitat suitability, climate
815and landscape structure. *Landscape Ecology*, 21(7), 989–1001.
816<https://doi.org/10.1007/s10980-005-6057-7>

817Serruys, M., & Van Dyck, H. (2014). Development, survival, and phenotypic plasticity in
818anthropogenic landscapes: Trade-offs between offspring quantity and quality in the nettle-
819feeding peacock butterfly. *Oecologia*, 176(2), 379–387. <https://doi.org/10.1007/s00442-014-8203016-5>

821Settele, J., Kudrna, O., Harpke, A., Kühn, I., van Swaay, C., Verovnik, R., Warren, M.,
822Wiemers, M., Hanspach, J., Hickler, T., Kühn, E., van Halder, I., Veling, K., Vliegenthart, A.,
823Wynhoff, I., & Schweiger, O. (2008). Climatic Risk Atlas of European Butterflies. *BioRisk*, 1,
8241–712. <https://doi.org/10.3897/biorisk.1>

825Shama, L. N. S. (2015). Bet hedging in a warming ocean: Predictability of maternal
826environment shapes offspring size variation in marine sticklebacks. *Global Change Biology*,
82721(12), 4387–4400. <https://doi.org/10.1111/gcb.13041>

828Shipp, J. L., & Gillespie, T. J. (1993). Influence of Temperature and Water Vapor Pressure
829Deficit on Survival of *Frankliniella occidentalis* (Thysanoptera: Thripidae). *Environmental*
830*Entomology*, 22(4), 726–732. <https://doi.org/10.1093/ee/22.4.726>

831Shreeve, T. G. (1986a). The effect of weather on the life cycle of the speckled wood butterfly
832Pararge aegeria. *Ecological Entomology*, 11(3), 325–332. <https://doi.org/10.1111/j.1365->
8332311.1986.tb00309.x

834Shreeve, T. G. (1986b). Egg-laying by the speckled wood butterfly (Pararge aegeria): The role
835of female behaviour, host plant abundance and temperature. *Ecological Entomology*, 11(2),
836229–236. <https://doi.org/10.1111/j.1365-2311.1986.tb00298.x>

837Suggitt, A. J., Gillingham, P. K., Hill, J. K., Huntley, B., Kunin, W. E., Roy, D. B., &
838Thomas, C. D. (2011). Habitat microclimates drive fine-scale variation in extreme
839temperatures. *Oikos*, 120(1), 1–8. <https://doi.org/10.1111/j.1600-0706.2010.18270.x>

840Süle, G., Balogh, J., Fóti, S., Gecse, B., & Körmöczi, L. (2020). Fine-Scale Microclimate
841Pattern in Forest-Steppe Habitat. *Forests*, 11(10), 1078. <https://doi.org/10.3390/f11101078>

842Tarrant, C. A., & McCoy, C. W. (1989). Effect of Temperature and Relative Humidity on the
843Egg and Larval Stages of Some Citrus Root Weevils. *The Florida Entomologist*, 72(1), 117.
844<https://doi.org/10.2307/3494976>

845Taylor, S. H., Franks, P. J., Hulme, S. P., Spriggs, E., Christin, P. A., Edwards, E. J.,
846Woodward, F. I., & Osborne, C. P. (2012). Photosynthetic pathway and ecological adaptation
847explain stomatal trait diversity amongst grasses. *New Phytologist*, 193(2), 387–396.
848<https://doi.org/10.1111/j.1469-8137.2011.03935.x>

849Terando, A. J., Youngsteadt, E., Meineke, E. K., & Prado, S. G. (2017). Ad hoc
850instrumentation methods in ecological studies produce highly biased temperature
851measurements. *Ecology and Evolution*, 7(23), 9890–9904. <https://doi.org/10.1002/ece3.3499>

852Tetens, O. (1930). Ueber einige meteorologische Begriffe. *Journal of Geophysics*, 6, 297–309.

853Tropek, R., Cizek, O., Kadlec, T., & Klecka, J. (2017). Habitat Use of *Hipparchia semele*
854(Lepidoptera) in Its Artificial Stronghold: Necessity of the Resource-Based Habitat View in
855Restoration of Disturbed Sites. *Polish Journal of Ecology*, 65(3), 385–399.
856<https://doi.org/10.3161/15052249PJE2017.65.3.006>

857Turlure, C., Choutt, J., Baguette, M. and Van Dyck, H. (2010). Microclimatic Buffering and
858Resource-Based Habitat in a Glacial Relict Butterfly: Significance for Conservation under
859Climate Change: Microclimatic Buffering in a Relict Butterfly. *Global Change Biology*,
86016(6):1883–93. doi: 10.1111/j.1365-2486.2009.02133.x.

861Turlure, C., Schtickzelle, N., Dubois, Q., Baguette, M., Dennis, R. L. H., & Van Dyck, H.
862(2019). Suitability and Transferability of the Resource-Based Habitat Concept: A Test With
863an Assemblage of Butterflies. *Frontiers in Ecology and Evolution*, 7:127. doi:
86410.3389/fevo.2019.00127.

Vandewoestijne, S., & Van Dyck, H. (2010). Population Genetic

865 Differences along a Latitudinal Cline between Original and Recently Colonized Habitat in a
866 Butterfly. *PLoS ONE*, 5(11), e13810. <https://doi.org/10.1371/journal.pone.0013810>

867 Vermunt, B., Cuddington, K., Sobek-Swant, S., Crosthwaite, J. C., Lyons, D. B., & Sinclair,
868 B. (2012). Temperatures experienced by wood-boring beetles in the under-bark microclimate.
869 *Forest Ecology and Management*, 269, 149–157. <https://doi.org/10.1016/j.foreco.2011.12.019>

870 Van Dyck, H. (2012). Changing Organisms in Rapidly Changing Anthropogenic Landscapes:
871 The Significance of the ‘Umwelt’-Concept and Functional Habitat for Animal Conservation:
872 Perception and Habitat in Anthropogenic Landscapes. *Evolutionary Applications*, 5(2):144–
873 53. doi: 10.1111/j.1752-4571.2011.00230.x.

874 von Arx, G., Graf Pannatier, E., Thimonier, A., & Rebetez, M. (2013). Microclimate in
875 forests with varying leaf area index and soil moisture: Potential implications for seedling
876 establishment in a changing climate. *Journal of Ecology*, 101(5), 1201–1213.
877 <https://doi.org/10.1111/1365-2745.12121>

878 Whittaker, R. H. (1975). *Communities and ecosystems*.
879 New York, NY: Macmillan Publishers.

879 Wiens, J. J., & Graham, C. H. (2005). Niche Conservatism: Integrating Evolution, Ecology,
880 and Conservation Biology. *Annual Review of Ecology, Evolution, and Systematics*,
881 36(1):519–39. doi: 10.1146/annurev.ecolsys.36.102803.095431.

882 Williams, N. M., & Winfree, R. (2013). Local habitat characteristics but not landscape
883 urbanization drive pollinator visitation and native plant pollination in forest remnants.
884 *Biological Conservation*, 160, 10–18. <https://doi.org/10.1016/j.biocon.2012.12.035>

885 Willmer, P. G. (1982). Microclimate and the Environmental Physiology of Insects. *Advances*
886 *in Insect Physiology*, 16, 1–57. [https://doi.org/DOI: 10.1016/S0065-2806\(08\)60151-4](https://doi.org/DOI: 10.1016/S0065-2806(08)60151-4)

887 Wilson, E. O. (1992). *The Diversity of Life*. Cambridge, MA: Harvard University Press.

888 Wilson, R. J., Davies, Z. G., & Thomas, C. D. (2010). Linking Habitat Use to Range
 889 Expansion Rates in Fragmented Landscapes: A Metapopulation Approach. *Ecography*,
 890 33(1):73–82. doi: 10.1111/j.1600-0587.2009.06038.x.

891 Woods, H. A. (2013). Ontogenetic changes in the body temperature of an insect herbivore.
 892 *Functional Ecology*, 27(6), 1322–1331. <https://doi.org/10.1111/1365-2435.12124>

893 Xia, S., Dweck H. K. M., Lutomiah J., Sang, R., McBride, C. S., Rose, N. H., Ayala, D., &
 894 Powell, J. R. (2021). Larval Sites of the Mosquito *Aedes Aegypti* Formosus in Forest and
 895 Domestic Habitats in Africa and the Potential Association with Oviposition Evolution.
 896 *Ecology and Evolution*, 11(22):16327–16343. doi: 10.1002/ece3.8332.

897 Yan, J. (2019). Testing an energy exchange and microclimate cooling hypothesis for the
 898 effect of vegetation configuration on urban heat. *Agricultural and Forest Meteorology*, 11.
 899 Zhang, H., & Wu, J. (2002). A statistical thermodynamic model of the organizational order of
 900 vegetation. *Ecological Modelling*, 153(1–2), 69–80. [https://doi.org/10.1016/S0304-](https://doi.org/10.1016/S0304-9013800(01)00502-6)
 901 3800(01)00502-6

902 Zhang, W., Chang, X.-Q., Hoffmann, AryA., Zhang, S., & Ma, C.-S. (2015). Impact of hot
 903 events at different developmental stages of a moth: The closer to adult stage, the less
 904 reproductive output. *Scientific Reports*, 5(1), 10436. <https://doi.org/10.1038/srep10436>

905 Zhang, Y. (2017). Optimizing green space locations to reduce daytime and nighttime urban
 906 heat island effects in Phoenix, Arizona. *Landscape and Urban Planning*, 10. [http://dx.doi.org/](http://dx.doi.org/10.1016/j.landurbplan.2017.04.009)
 907 10.1016/j.landurbplan.2017.04.009

908TABLES

909**Table 1.** Variable contributions to the principal components PC1 and PC2. Loadings are
 910indicated as percentages relative to PC1 and PC2. Rows are ordered along descending ratio of
 911% contributing to PC1 relative to % contributing to PC2. In grey are contributions of >20%.
 912T: temperature; RH: relative humidity, VPD: vapour pressure deficit.

913	<i>PC1</i>	<i>PC2</i>
914	<i>(59 %)</i>	<i>(19 %)</i>
<i>Minimum RH</i>	88 % (-)	0 % (-)
<i>Day mean VPD</i>	92 %	1 % (-)
<i>Day mean T</i>	79 %	1 % (-)
<i>Range RH</i>	83 %	1 %
<i>Standard deviation RH</i>	77 %	3 %
<i>Standard deviation VPD</i>	91 %	4 %
<i>Maximum VPD</i>	83 %	7 %
<i>Range VPD</i>	83 %	8 %
<i>Day mean RH</i>	77 % (-)	7 %
<i>Maximum T</i>	72 %	10 %
<i>Standard deviation T</i>	61 %	26 %
<i>Range T</i>	44 %	41 %
<i>Night mean VPD</i>	42 %	46 % (-)
<i>Night mean RH</i>	39 % (-)	44 %
<i>Night mean T</i>	27 %	47 % (-)
<i>Minimum VPD</i>	6 %	21 % (-)
<i>Maximum RH</i>	4 % (-)	16 %
<i>Minimum T</i>	11 %	50 % (-)

Table 2. Landscape type differences for the two variables that contributed to most of the variation of PC1 and PC2, respectively, and for two proxy measures of microclimatic predictability. Relative contributions to PC1 or PC2 are shown between brackets. The table presents a pairwise comparison among least square means among the three landscape types, based on linear mixed model output with week (N=6) as a random effect. Numerator and denominator degrees of freedom for all estimates are 2 and 127 respectively. ‘*’: logarithmically transformed in the linear mixed model.

Main variables PC1								
<i>Predictors</i>	Standard deviation VPD*				Day VPD*			
	(91.06%)				(91.80%)			
	<i>Estimates</i>	<i>SE</i>	<i>t.ratio</i>	<i>p</i>	<i>Estimates</i>	<i>SE</i>	<i>t.ratio</i>	<i>p</i>
agri - urban	0.19	0.068	2.78	0.019	0.15	0.072	2.037	0.13
agri - forest	0.27	0.072	3.81	0.0006	0.26	0.076	3.46	0.002
urban - forest	0.083	0.071	1.17	0.73	0.12	0.076	1.53	0.39

Main variables PC2								
<i>Predictors</i>	Minimum night temperature				Night temperature			
	(50.23%)				(47.03%)			
	<i>Estimates</i>	<i>SE</i>	<i>t.ratio</i>	<i>p</i>	<i>Estimates</i>	<i>SE</i>	<i>t.ratio</i>	<i>p</i>
agri - urban	-1.12	0.278	-4.038	0.0003	-0.72	0.23	-3.18	0.006
agri - forest	-0.51	0.29	-1.73	0.26	-0.051	0.24	-0.21	1
urban - forest	0.62	0.29	2.13	0.11	0.67	0.24	2.83	0.016

VPD predictability								
<i>Predictors</i>	Day-to-day VPD variability				Short-term VPD variability			
	<i>Estimates</i>	<i>SE</i>	<i>t.ratio</i>	<i>p</i>	<i>Estimates</i>	<i>SE</i>	<i>t.ratio</i>	<i>p</i>
	<i>Estimates</i>	<i>SE</i>	<i>t.ratio</i>	<i>p</i>	<i>Estimates</i>	<i>SE</i>	<i>t.ratio</i>	<i>p</i>
agri - urban	0.19	0.095	1.98	0.15	0.19	0.073	2.55	0.035
agri - forest	0.29	0.1	2.9	0.013	0.29	0.076	3.75	0.0008
urban - forest	0.1	0.099	1.015	0.94	0.1	0.076	1.32	0.57

FIGURE LEGEND

Fig. 1: Overview of the sample sites. a: Twelve sample locations in and around four Belgian cities that are characterized by agricultural (square), urban (triangle) or woodland (circle) landscape settings. Crosses represent nearby weather stations from The Royal Meteorological Institute of Belgium in Melle (M), Zaventem (Z) and Bauvechevain (B). Altitude of all weather locations Grey lines depict Belgian borders. White coloration in the upper left represents the North Sea and Easter Scheldt region. Altitude (in meter above sea level) for all sample locations and weather stations are (from West to East): 15, 8, 18, 62, 60, 73, 61, 45, 155, 49, 86, 87, 59, 33, 101. b,c & d: examples of sample locations for forest, urban and agricultural landscape types, respectively. Green shading represents woodland cover. Diamond marks indicate sample sites and numbers below the marks represent the week during which measures were made, with week 1 starting on the 13th of June 2018. e: sample site with HOBO U23 v2 climatic sensor placed 12 cm above ground in the grass layer.

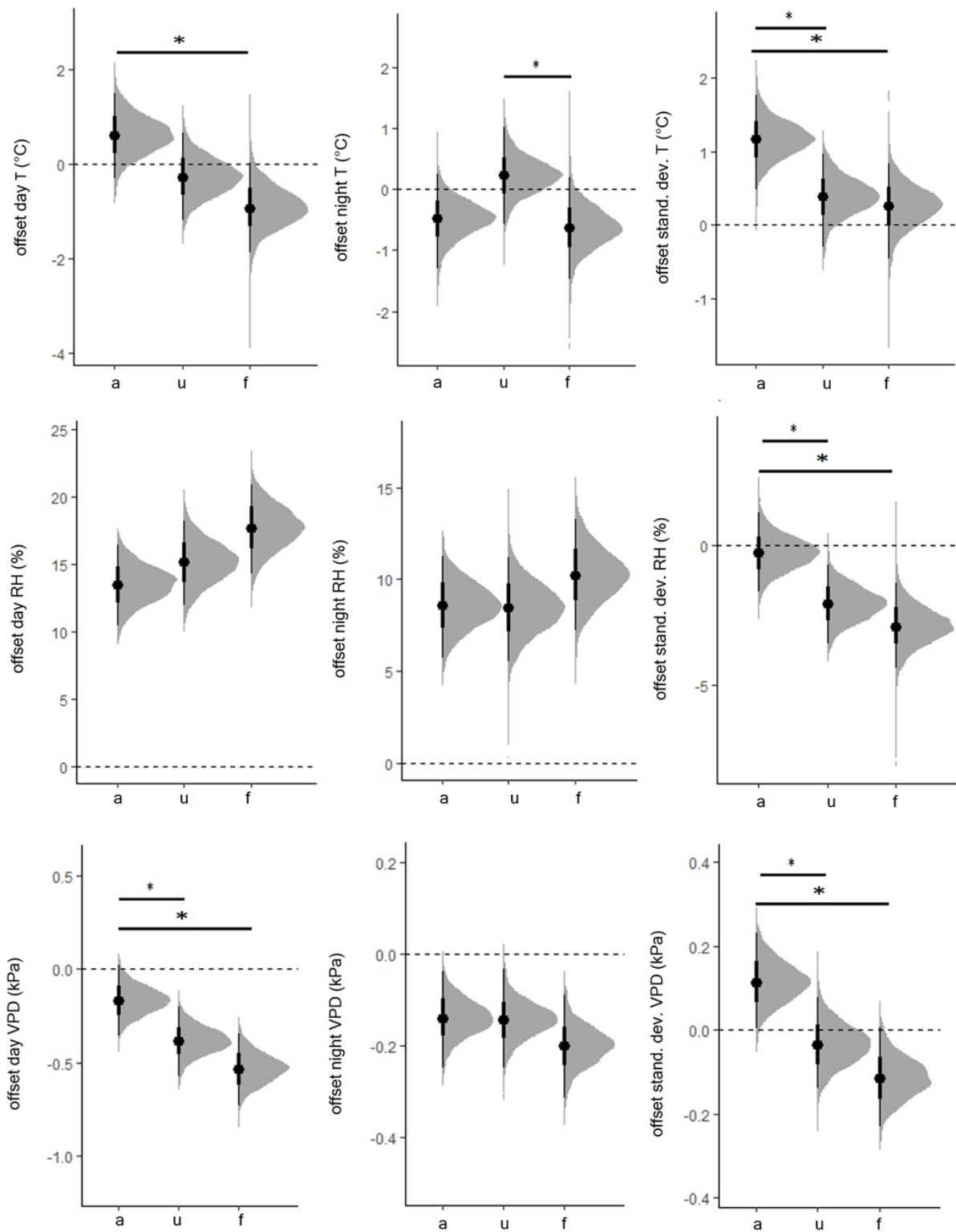
936

Fig. 2. Posterior distribution of the landscape type-related estimates of the nine microclimatic variables. Thick lines mark the posterior 66%-credible interval around the mean. Thin lines mark the posterior 95%-credibility interval around the mean. When this line crosses the dashed line at zero, there is no difference between the HOBO sensor data and the weather station data within the 95%-credibility interval. 'u': urban; 'f': forest; 'a': agricultural (intercept). Horizontal lines with asterisks indicate differences in which the value tested against lies outside the 98.33% credibility interval.

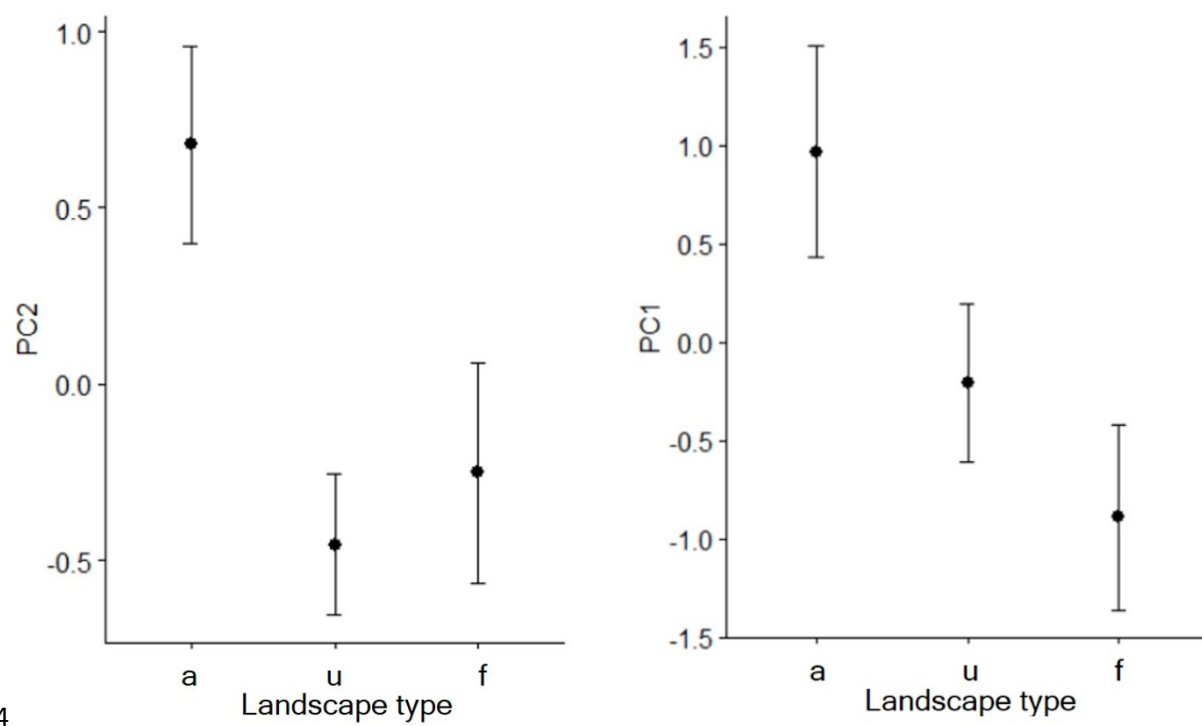
Fig. 3. Mean value (\pm SE) of the first two principal components representing climatic variability relative to landscape type. A high PC1-score (explained 59 %) corresponds to variables that relate to hot and dry daytime conditions and stronger fluctuations during the day. A high PC2-score (explained 19%) corresponds to colder and more humid night

948conditions. a: agriculture; u: urban; f: forest. Horizontal lines with asterisks indicate
949differences with Bonferroni-corrected p-values lower than 0.02 (*) or 0.002 (**).

950



953Figure



954