

1 **Mapping spatial microclimate patterns in mountain forests from LiDAR**

2 Michiel Vandewiele¹, Lisa Geres^{2,3}, Annette Lotz², Lisa Mandl^{1,2}, Tobias Richter^{1,2},

3 Sebastian Seibold^{1,2,4}, Rupert Seidl^{1,2}, and Cornelius Senf^{1,*}

4 ¹Technical University of Munich, School of Life Sciences, Ecosystem Dynamics and Forest
5 Management Group, Hans-Carl-von-Carlowitz-Platz 2, 85354 Freising, Germany

6 ²Berchtesgaden National Park, Doktorberg 6, 83471, Berchtesgaden, Germany

7 ³Goethe University Frankfurt, Faculty of Biological Sciences, Institute for Ecology,
8 Evolution and Diversity, Conservation Biology - 60438 Frankfurt Am Main, Germany

9 ⁴Technische Universität Dresden, Faculty of Environmental Sciences, Forest Zoology,

10 Piener Str. 7, 01737 Tharandt, Germany

11 *corresponding author: cornelius.senf@tum.de

14 **Abstract:** Forests create unique microclimates that have the potential to serve as microrefugia
15 for species under climate change. Yet, our understanding of the heterogenous thermal
16 patterns at the forest floor of complex landscapes (e.g., in mountain forests) remains
17 incomplete. We here used Light Detection and Ranging (LiDAR) for predicting summer
18 temperature offsets in a mountain forest landscape in the European Alps. We calibrated
19 models on a network of 150 microclimate loggers that were combined with data from 15
20 meteorological stations to estimate the maximum, mean, and minimum temperature offsets,
21 using LiDAR-derived metrics of forest structure and topography as predictors. Models
22 predicted summer temperature offsets with an R^2 /RMSE of 0.50/3.15 °C for maximum
23 temperature, 0.51/0.41 °C for mean temperature and 0.55/0.57 °C for minimum temperature.
24 Forest canopy openness and elevation were most important for predicting temperature offsets.
25 The mean offset ranged from - 1.9 °C to 2.7 °C (mean of - 0.3 °C), but both minimum and
26 maximum offsets varied considerably, with some forests even having warmer maximum and
27 colder minimum temperatures than open areas. This was particularly prominent in forests of
28 the subalpine zone, which are characterized by open canopies and a considerable presence of
29 coniferous shrubs. In contrast, submontane forests with largely closed canopies had mostly
30 colder maximum and warmer minimum temperatures within forests compared to open areas.
31 Analysing the development of temperature offsets with time since disturbance, we found that
32 recently disturbed forests had higher maximum temperatures compared to open areas, but
33 they recovered to closed forest conditions within two decades. We conclude that mountain
34 forests exhibit complex microclimate patterns that vary strongly with forest type and canopy
35 openness. We further highlight that disturbances are an important driver of spatiotemporal
36 dynamics in forest microclimate. Finally, temperature offset maps such as the ones generated
37 here have strong potential to improve the robustness of species distribution models and to
38 assess climate risks for biodiversity.

39 **Keywords:** Temperature offset, forest floor climate, climate extremes, remote sensing, forest
40 disturbance

42 **Introduction**

43 Climate change has profound impacts on terrestrial ecosystems globally (Sheridan and
44 Bickford 2011; Roulin 2014; Visser and Both 2005; Walther et al. 2002; Scheffers et al. 2016).
45 One possible response of many mobile species is to shift their locations towards the poles and
46 higher elevations to stay within their climatic niche (Lenoir et al. 2020; Chen et al. 2011; Chen
47 et al. 2009). Climate change will thus likely lead to a redistribution of life on Earth and the
48 emergence of novel biological communities (Lenoir et al. 2020; Pecl et al. 2017). Yet, not all
49 taxa shift their distribution proportionally to climatic change, with some taxa – particularly
50 endothermic organisms and plants – lagging behind macroclimatic warming trends, while
51 others respond more strongly than what can be expected from changes in temperature alone
52 (Bässler et al. 2013; Lenoir et al. 2020). Consequently, the transformation of species
53 assemblages towards thermophile taxa, as well as the general shift of species towards the poles
54 and higher elevations is often more complex than changes in temperature predict (Devictor et
55 al. 2012; Bertrand et al. 2011; Dullinger et al. 2012; Scheffers et al. 2014; Ash, Givnish, and
56 Waller 2017). One of the potential reasons for this divergence is the local climate regulating
57 function of vegetation, which is particularly pronounced in forest ecosystems, creating distinct
58 local microclimates that determine the climatic conditions perceived by many species (De
59 Frenne et al. 2021; Lembrechts, Nijs, and Lenoir 2019).

60 Forests cover nearly one third of the global terrestrial land surface and play a crucial
61 role in modulating species' responses to climate warming (FAO 2020; De Frenne et al. 2021).
62 For instance, forests buffer temperature maxima on average by 4 °C compared to open lands
63 (De Frenne et al. 2019). The microclimate in forests thus differs from macroclimate, mainly
64 due to vegetation increasing evapotranspiration and air mixing, as well as intercepting solar
65 radiation (Geiger, Aron, and Todhunter 2009; De Frenne et al. 2021). In addition, many
66 forested areas have complex structural (e.g., downed deadwood, snags) and micro-
67 topographical features (e.g., pit-and-mound structures) that further can modulate
68 microclimatic conditions (Jucker et al. 2018; Dobrowski 2011). The distinct thermal

69 environments in forests can further serve as microrefugia under climate change, because
1
2 70 microclimates in forests tend to change at a slower rate than in open lands (De Frenne et al.
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4 71 2013; De Frenne et al. 2019; Scheffers, Phillips, and Shoo 2014). The absolute difference
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6 72 between within-stand and open-land temperatures is termed temperature offset, and serves as
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8 73 a measure of how well forests buffer open-land temperatures and especially macroscale climate
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10 74 extremes (De Frenne et al. 2021; De Frenne et al. 2019; Zellweger, Coomes, et al. 2019). While
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12 75 other measures of microclimatic buffering exist (Gril et al. 2022), we here adopt this simple
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14 76 definition and refer to temperature offset in the following when addressing the absolute
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16 77 difference between within-stand and open-land temperatures.
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21 78 Despite the growing body of research supporting the significance of forests for
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23 79 offsetting temperature extremes, ecological research assessing biotic responses to increasing
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25 80 temperatures has largely relied on low-resolution climate data representing open conditions
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27 81 (Bramer et al. 2018). This data is typically derived from standardized meteorological weather
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29 82 stations, which record temperatures in open areas at 1.2 m to 2 m above ground in order to
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31 83 represent macroclimatic conditions (WMO 2008). However, these conditions differ from the
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33 84 microclimatic conditions in forests; they are thus often not representative for the thermal
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35 85 environment that forest-dwelling species experience (Potter, Arthur Woods, and Pincebourde
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37 86 2013; De Frenne et al. 2021). This discrepancy might partly explain why the observed
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39 87 response of many biotic systems differs from expectations derived from models driven with
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41 88 macroclimate data (Abbass et al. 2022; De Frenne et al. 2019; Willis and Bhagwat 2009;
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43 89 Lembrechts, Nijs, and Lenoir 2019; Moritz and Agudo 2013). Hence, to better understand
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45 90 biotic responses to increasing temperatures and to improve projections of climate change
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47 91 effects, a better understanding of the spatial variability in forest microclimate is needed.
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54 92 Forest structure, that is the horizontal and vertical distribution of vegetation, plays a
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56 93 crucial role for modulating forest microclimate. Numerous studies have shown that a decrease
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58 94 in canopy cover causes temperature offsets to decrease, which highlights the importance of
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60 95 canopy cover in modulating forest microclimate (De Lombaerde et al. 2022; Frey et al. 2016;
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96 De Frenne et al. 2019; Zellweger, Coomes, et al. 2019). Similarly, other structural features –
1 97 such as multiple tree layers or downed and standing deadwood – might influence forest
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4 98 microclimates, but their effects are less well understood (Thom et al. 2020; Kovács, Tinya, and
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7 99 Ódor 2017; De Frenne et al. 2021). Forest structure is often contingent on the prevailing
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9 100 forest type, which can thus serve as proxy of forest microclimatic temperature offsets. A study
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11 101 by Renaud et al. (2011), for instance, found that the temperature offsets of mountain forests
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13 102 were lowest for pine forests, which are open in structure, and highest for deciduous forests
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15 103 with closed canopies. Furthermore, forest disturbances can temporally alter forest structure
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17 104 by opening up the canopy and altering the prevalence of open and closed forest developmental
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19 105 stages at the landscape scale (Senf et al. 2020; Senf, Sebald, and Seidl 2021). Yet, both the
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21 106 effects of forest type and disturbance on microclimate are not fully understood (Schwartz et
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23 107 al. 2022; Ewers and Banks-Leite 2013; Gavito et al. 2021; Sánchez-Reyes et al. 2021; Thom et
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25 108 al. 2020; Aragón et al. 2015; Renaud et al. 2011). Focusing on the effects of forest type and
26
27 109 disturbance is important, as climate change could cause substantial shifts in both tree species
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29 110 distribution and disturbance regimes (Thom et al. 2022; Thom and Seidl 2022; Albrich et al.
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31 111 2022). If disturbances increase under climate change, for instance, this could create negative
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33 112 feedbacks between climate change and temperature offsets in forests, potentially rendering
34
35 113 future forests unsuitable as microclimate refugia (De Frenne et al. 2021). Those negative
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37 114 feedbacks might include the loss of intact tree canopy following stand-replacing disturbances
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39 115 (Senf and Seidl 2021) or more subtle changes in forest structure such as shorter and more
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41 116 open forests under increasing disturbances (Stritih et al. 2023). Understanding the feedback
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43 117 processes between microclimates, changing forest types and disturbance regimes requires the
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45 118 consideration of spatial and temporal variability in forest microclimates at the landscape scale.
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47 119 However, there is still a lack of microclimate studies that go beyond the plot or stand scale,
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49 120 considering variability in microclimate in relation to landscape-scale variation in forest type
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51 121 and disturbance.
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122 Remote sensing offers a way forward in understanding landscape-level variation in
1 microclimate by means of upscaling local in-situ measurements to the landscape scale (Senf
2 123 2022; Zellweger, De Frenne, et al. 2019). While measurements from in-situ microclimate
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4 124 loggers are the gold standard for capturing microclimatic conditions on the ground, they only
5
6 125 record conditions for a single point in space and – depending on the sampling design – their
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8 126 measurements might not be representative of the full landscape (e.g., when plot locations were
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10 127 stratified along an elevation gradient). Observations from microclimate loggers alone might
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12 128 thus give biased estimates of the thermal characteristics of a full landscape. Remote sensing
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14 129 provides spatially continuous information on vegetation properties that can be used to infer
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16 130 microclimatic conditions in a spatially explicit manner, thus complementing networks of
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18 131 microclimate loggers (Zellweger, De Frenne, et al. 2019). Light detection and ranging
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20 132 (LiDAR) is of particular use for quantifying temperature offsets across forest landscapes, due
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22 133 to its ability to represent vertical and horizontal forest structure as well as local topographic
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24 134 features (Jucker et al. 2018). In fact, several studies have shown great potential for mapping
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26 135 forest microclimate from LiDAR (Zellweger, Coomes, et al. 2019; Frey et al. 2016; Kašpar et
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28 136 al. 2021; Lenoir, Hattab, and Pierre 2017; Davis et al. 2019), but those studies either used
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30 137 drone-based data with limited spatial extent or limited the analysis to relatively few simple
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32 138 metrics of canopy cover. Furthermore, most previous works have focused on topographically
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34 139 simple landscapes. It thus remains unclear whether using LiDAR data to map temperature
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36 140 offsets in topographically more complex forest landscapes, such as found in the European Alps,
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38 141 is also feasible.
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42 143 The aim of this study is to quantify the spatial patterns of temperature offsets in mountain
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44 144 forests using airborne LiDAR data in combination with a large network of microclimate
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46 145 loggers and weather stations, focussing in particular on temperature offsets during summer.
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48 146 We approach this aim by addressing four specific objectives: (1) Testing whether summer
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50 147 temperature offsets in mountain forests can be mapped from airborne LiDAR data. (2)
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52 148 Quantifying the relative importance of forest structural and topographic variables for
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149 predicting summer temperature offsets. (3) Characterizing the effect of forest types on summer
150 temperature offsets at the landscape scale. (4) Assessing the effect of past forest disturbances
151 on summer temperature offsets at the landscape scale. We expect high resolution LiDAR data
152 to be well-suited for mapping temperature offsets in complex terrain, with forest structure
153 being more important than topography, because forest structure is the main determinant of
154 how much incoming solar radiation reaches the forest floor. Yet, topographic variability in
155 mountain forests is high, which might increase the importance of local topographic features.
156 We further expect that the temperature offsets are most pronounced in submontane forests
157 characterized by high canopy cover and less pronounced in subalpine forests that are naturally
158 open (Renaud et al. 2011). Finally, we anticipate that temperature offsets are reduced in
159 recently disturbed sites and increase with forest development due to increasing canopy closure
160 over the successional trajectory (Zenner et al. 2016).

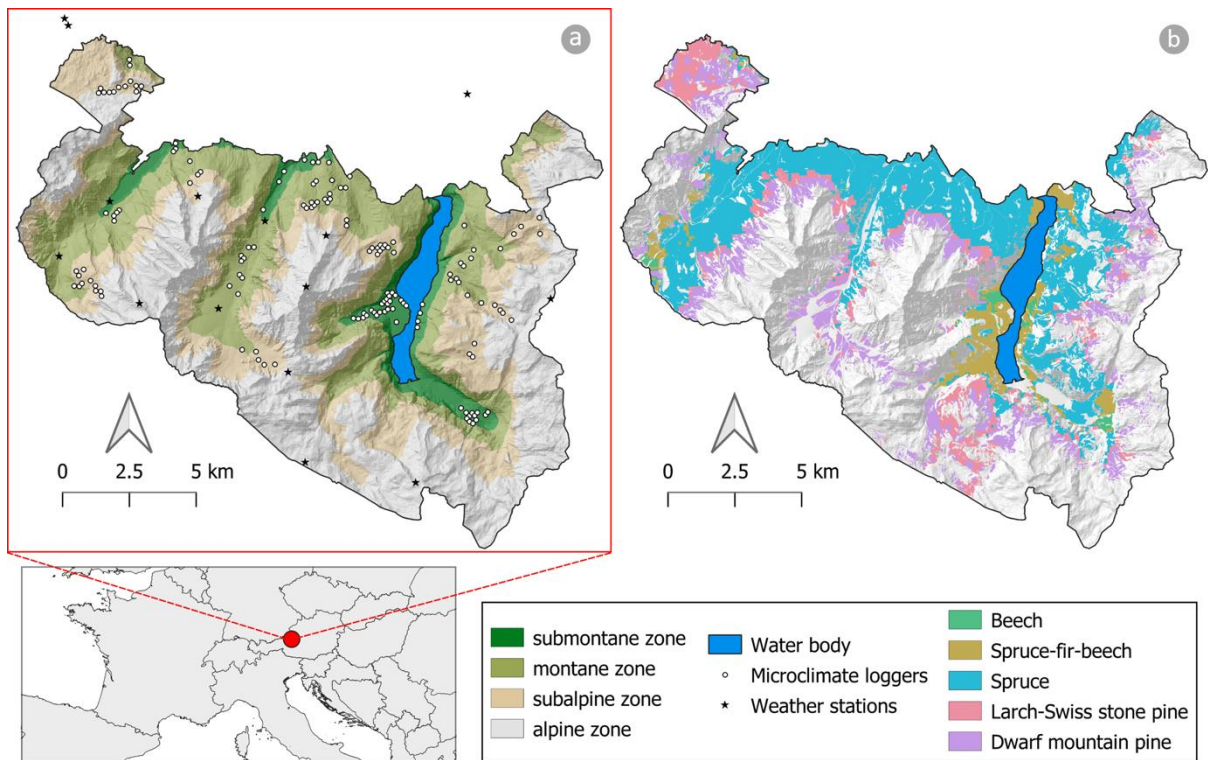
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162 **Methods**

163 ***Study area***

164 The study was carried out at Berchtesgaden National Park, a 20'808 ha landscape in the
165 German Alps with 8'645 ha of forests. The area has a long history of intense forest
166 management, which ceased in 1978 with the establishment of the national park. Since then,
167 there has been no forest management in 75 % of the area, allowing for the analysis of natural
168 forest dynamics without human influence. The study area is topographically complex,
169 spanning an elevation gradient from 603 m a.s.l. (Lake Königssee) to 2713 m a.s.l. (mount
170 Watzmann). In the submontane zone (below 850 m a.s.l.) natural vegetation is dominated by
171 European beech (*Fagus sylvatica* L.). The montane zone between 850 m and 1400 m a.s.l. is
172 naturally covered by mixed forests, which typically contain Norway spruce (*Picea abies* (L.)
173 Karst.), European beech and silver fir (*Abies alba* Mill.). Due to the long history of forest use
174 in the area, Norway spruce is currently dominating large parts of the submontane and

175 montane zones. In the subalpine zone between 1400 m a.s.l. and the treeline at approximately
 176 1700 m a.s.l., Norway spruce forests as well as European larch (*Larix decidua* Mill.) and Swiss
 177 stone pine (*Pinus cembra* L.) forests prevail. Finally, the timberline ecotone is dominated by
 178 dwarf mountain pine (*Pinus mugo ssp. mugo* Turra) (Thom et al. 2022; Thom and Seidl 2022)
 179 (Figure 1).



182 **Figure 1:** The location of Berchtesgaden National Park with (a) the locations of
 183 microclimate loggers (white dots with black circles) and weather stations (black stars), and
 184 (b) the current distribution of forest types according to Thom et al. (2022).

186 *Temperature measurements and offset estimation*

187 We calculated temperature offsets from a network of microclimate loggers and macroclimate
 188 weather stations distributed throughout Berchtesgaden National Park (Figure 1a).
 189 Microclimatic temperature was recorded from July 8th until August 31st 2021 using 150
 190 Tomst TMS-4 loggers. The loggers recorded the temperature at -6, 2 and 15 cm height above

191 ground every 15 minutes (Wild et al. 2019). Here, we used the temperature measured at 15
192 cm above ground to characterize forest microclimate (Haesen et al. 2021). Microclimate
193 loggers were installed at the centre of 500 m² circular forest inventory plots stratified along
194 three elevation zones (submontane, montane, subalpine) and five forest developmental stages,
195 with ten replica per combination (resulting in 150 loggers in total). Forest development stages
196 were classified according to Zenner et al. (2016), distinguishing gap/regeneration,
197 establishment, optimum, plenter, and terminal/decay stages. This stratification allowed for a
198 broad representation of all forest types and forest development stages in the landscape.
199 Macroclimate temperature at a minimum of 2 m height above ground was recorded in 10-
200 minute intervals at 15 weather stations operated by the national park and the Bavarian
201 Avalanche Service. These weather stations cover the entire elevation gradient of the landscape
202 and are evenly distributed over the national park area (including nearby locations outside of
203 the national park boundaries, Figure 1a).

204 To calculate temperature offsets, we first averaged the temperature data from
205 microclimate loggers and weather stations to hourly values as the arithmetic mean. Second,
206 to obtain macroclimatic temperatures for the location of each microclimate logger, we
207 interpolated hourly macroclimatic temperatures using adiabatic lapse rates. This was achieved
208 with linear regression models based on elevation and temperature records from the 15
209 macroclimate weather stations (Figure 1). We calculated individual lapse rates for each hour
210 of the observation period (a total of 99'000 models). These models were robust, except for a
211 few points in time, with a median R² of 0.93 (range: 0.11 – 1.00) and an average root mean
212 square error (RMSE) of 0.95 °C (range: 0.26 – 3.79 °C). The average adiabatic lapse rate
213 was 0.56 °C/100 m with a standard deviation of 0.16 °C/100 m. From these models the we
214 interpolated macroclimatic temperatures for each microclimate sensor location based on its
215 elevation. Third, we calculated the minimum, mean and maximum temperature for both the
216 micro- and macroclimate record over the full observation period (July 8th until August 31st
217 2021). We finally calculated the temperature offset as the difference between the minimum,

218 mean, and maximum microclimatic and interpolated macroclimatic temperature, respectively.

219 Negative temperature offset values signify colder within-stand than open-land temperatures.

220 *LiDAR-based predictor variables*

221 Two groups of predictor variables – one representing forest structure and the other

222 representing topography – were derived from airborne LiDAR data. The data were acquired

223 during early September 2021 using a helicopter-mounted Riegel VQ-780i sensor with average

224 point density of ~ 50 points m^{-2} . Forest structure predictors were calculated from the LiDAR

225 point cloud, which was extracted around the location of each microclimate logger using a

226 12.6 m buffer, corresponding to a 500 m^2 plot area. We calculated a set of 36 potential metrics

227 summarizing the distribution and intensity of LiDAR returns using the *lidR* package in R

228 version 4.2.2 (Roussel et al. 2020; R Core Team 2019). From those 36 potential predictors, we

229 selected three candidate predictors based on a-priori ecological hypotheses and bivariate

230 correlation analysis (Table 1): the percent of lidar returns reaching the ground (hereafter

231 referred to as *canopy openness*), the average height of returns (hereafter referred to as *height*),

232 and the cumulative percentage of returns from the ground layer (i.e., the first of ten equally

233 spaced horizontal layers; see Table 1 and Roussel et al. 2020; hereafter referred to as *ground*

234 *vegetation density*). *Canopy openness* quantifies the amount of light reaching the forest floor, and

235 we hypothesize it to be positively correlated with mean and maximum temperature offsets and

236 negatively with minimum temperature offsets (Zellweger et al. 2019). *Height* indicates the

237 average height of trees and thus serves as a proxy for forest age and potential structural

238 complexity (with taller stands having a higher variability in individual tree heights; Atkins et

239 al. 2021). We expected this variable to correlate negatively with mean and maximum

240 temperature offsets and positively with minimum temperature offsets. *Ground vegetation density*

241 indicates the density and cover of forest floor vegetation. Here we had contrasting

242 expectations, with dense ground vegetation providing additional shadowing and evaporative

243 cooling (Stickley and Fraterigo 2021), but open layers of coniferous shrubs still allowing high

244 solar radiation to reach the ground while simultaneously reducing wind speeds. We thus did
1 not have a clear hypothesis on the direction of the correlation with temperature offsets.
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4 246 We used a digital elevation model with 1 m spatial resolution derived from LiDAR
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7 247 data for topography predictors. Potential topography predictors included seven metrics
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9 248 defined by Frey et al. (2016) for estimating microclimatic temperatures in mountainous
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11 249 regions. However, we found substantial multi-collinearity between those predictors and
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14 250 decided to only include the average slope and topographic index into our final model (see
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16 251 Table 1 for details). We calculated both metrics for each logger location using a 50 m circular
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18 252 extraction buffer. We used a larger buffer to account for surrounding topography features,
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21 253 such as local depressions. We tested different buffers in a preliminary analysis and found 50
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23 254 m to be best suited to capture local topographic conditions. We further obtained two
24
25 255 additional predictor variables characterizing potential solar irradiance from the solar
26
27 256 irradiance and irradiation model *r.sun* implemented in Grass GIS (Geographic Resources
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29 257 Analysis and Support System) (Hofierka and Suri 2002; Neteler et al. 2012). We ran the model
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31 258 on the same LiDAR-based DEM, but with a coarser resolution of 10 m x 10 m, to derive solar
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33 259 irradiation patterns for 12:00 and 16:00 on the 15th of July 2021, representing north-south and
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35 260 east-west gradients. As global, direct and diffuse incoming solar radiation were highly
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37 261 correlated, we decided to only use diffuse incoming solar radiation in the final model based on
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39 262 higher correlations with temperature offsets in a-priori bivariate correlation analyses. Finally,
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41 263 elevation was used as a control variable to account for its influence on overall climatic
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43 264 conditions that could modulate microclimate in mountainous terrain, such as wind speeds, but
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45 265 are unrelated to local factors (Dobrowski 2011; Meineri and Hylander 2017). We further
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47 266 included elevation as cofounder for both the structure and topographic variables, which show
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49 267 strong elevational patterns (i.e., shorter and more open forests in higher elevation areas;
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51 268 steeper and more rugged terrain in higher elevation areas).
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58 269 For creating temperature-offset maps for the entire forested landscape of
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61 270 Berchtesgaden National Park, we calculated the same predictors outlined above not only for
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271 the individual plots, but also for a regular 20 m x 20 m grid. While the size of the grid cells is
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 2 272 slightly below the plot size, we assume this difference to be negligible. We only predicted
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 4 273 offset values for forested grid cells, which we identified with an existing forest mask at 10 m
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 7 274 x 10 m resolution provided by the national park administration (see Figure 1 and Mandl
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 9 275 (2020)).

10
 11 276 **Table 1:** Overview of the forest structure and the topographic predictor variables used to
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 13
 14 277 model temperature offsets.

| Predictor | Definition |
|---------------------------|---|
| Structure | |
| Height | Mean absolute height of all LiDAR returns. |
| Canopy openness | Proportion of LiDAR returns classified as ground. Higher values thus indicate a sparser canopy with more returns reaching the forest floor. |
| Ground vegetation density | Cumulative percentage of returns in the 1 st of ten equally spaced horizontal layers. Higher values thus means a higher proportion of all returns returned by the lowest vegetation layer. |
| Topography | |
| Elevation | Elevation at the centre point of a plot |
| Topographic index | Difference between the elevation of the centre point and the average elevation of a plot (negative values: local low point/ positive values: local high point) |
| Slope | Average slope of a plot |

Diffuse incoming solar radiation at 12:00 Amount of solar energy falling on a surface that is scattered by atmospheric particles; representing conditions at 12:00.

Diffuse incoming solar radiation at 16:00 Amount of solar energy falling on a surface that is scattered by atmospheric particles; representing conditions at 16:00.

Modelling temperature offset

We modelled the average (TO_{mean}), minimum (TO_{min}), and maximum (TO_{max}) temperature offsets based on the forest structure and topography predictors described above using linear models in the R software environment (R Core Team 2019). We specifically used the following packages: *lidR*, *raster*, *rgdal*, *exactextractr*, *sf*, and *ggplot2* (Hijmans 2020; Keitt 2010; Baston 2020; Pebesma 2018; Wickham 2009). We also tested more complex models that can deal with non-linearities and potential interactions between variables (i.e., boosted regression trees, generalized additive models), but found linear models to outperform those more complex models. That said, we included elevation as second-order polynomial due to some non-linear patterns in the residuals. We assessed model performance by means of RMSE and R^2 using spatial block cross validation with plots clustered into ten spatial clusters based on their location (Valavi et al. 2019). Additionally, we extracted the standardized regression coefficient for each predictor variable as well as partial eta-squared values to assess the importance of each variable for predicting temperature offsets. We note here that our intention was to build a robust and accurate predictive model of temperature offsets and not to perform causal inference of underlying drivers. We thus recommend being cautious in applying causal interpretation to our model estimates. Finally, we used the calibrated linear models to make spatial predictions of the temperature offsets for the forested area of the national park.

298 ***Influence of disturbance and forest type***

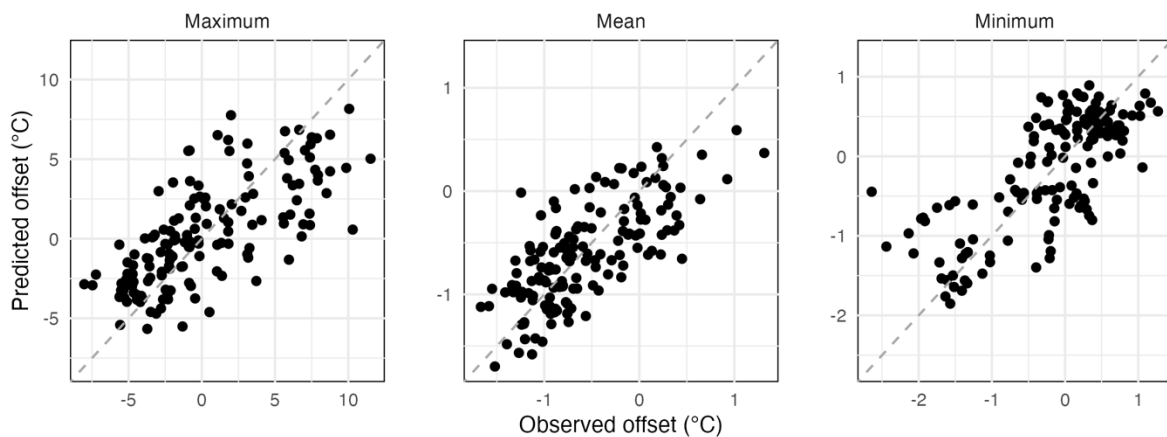
299 We compared the mapped temperature offset across past disturbances and forest types.
300 Specifically, we analysed our spatial predictions of temperature offset by overlaying a forest
301 disturbance map created by Senf and Seidl (2021), who used satellite data to map forest
302 disturbance for all of continental Europe at 30 m spatial resolution. The map contains the year
303 of the most severe forest disturbance from 1986 until 2020, which we extracted for all 20 m
304 grid cells where the centre point intersected a disturbance patch. We reclassified the
305 disturbance years from year of disturbance to time since disturbance (i.e., 2021 minus the
306 disturbance year) to obtain a chronosequence of temperature offset over post-disturbance
307 development (i.e. one to 35 years after disturbance). For statistical analyses, we grouped the
308 chronosequence in five-year bins. Similarly, we assessed the influence of forest type on the
309 temperature offset using a forest type map with a resolution of 1 ha created by Thom et al.
310 (2022) (Figure 1b). To exclude interacting effects between forest type and disturbance, we
311 only considered areas with restored forest canopies (i.e. without disturbance for the last 25
312 years) in the analysis of forest type effects (Senf, Müller, and Seidl 2019). Finally, we tested
313 what proportion of the overall spatial variation in temperate offsets can be explained by forest
314 type and time since disturbance, respectively, using analysis of variance.

316 **Results**

317 ***Temperature offset models and predictions***

318 The linear models predicted temperature offset with an $R^2/RSME$ of 0.50/3.15 °C for
319 maximum temperature, 0.51/0.41 °C for mean temperature and 0.55/0.57 °C for minimum
320 temperature (Figure 2). The temperature offset maps predicted by the models revealed a high
321 spatial variability in forest microclimate (Figure 3). Mean and maximum temperature offsets
322 were smaller or even reversed (warmer temperatures in forests compared to open lands) in
323 the subalpine zone, whereas forests in the montane and submontane zone showed overall
324 negative offsets for mean and maximum temperature (i.e., colder temperatures within stands

325 compared to macroclimatic temperatures). For the offset of minimum temperature, we found
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2 326 that minimum temperatures were warmer in submontane forests and colder in sub-alpine
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4 327 forests compared to open lands. Overall, landscape-scale maximum temperature offset ranged
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6 328 from - 7.5 to + 16.6 °C with a median of + 1.4 °C and a mean of + 1.6 °C. Mean temperature
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8 329 offsets ranged from - 1.9 to + 2.7 °C with a median of - 0.3 °C and a mean of - 0.3 °C. Minimum
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10 330 temperature offsets ranged from - 2.6 to + 1.2 °C with a median of - 0.5 °C and a mean of
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12 331 - 0.5 °C. Less than half of the forests in our study landscape showed negative summer
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14 332 maximum temperature offsets (36%) (i.e., colder temperatures in forests than in open land),
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16 333 whereas three quarters did show negative mean temperature offsets (75%). For minimum
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18 334 temperatures, 76 % of temperature offsets were negative (i.e., colder minimum temperatures
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20 335 in forests than in open lands), with 24% of the forests showing warmer minimum temperatures
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22 336 in forests than open lands.
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338 **Figure 2:** Observed versus predicted daytime temperature offsets for maximum, mean and
339 minimum summer temperatures. The grey lines represent the 1:1 lines.
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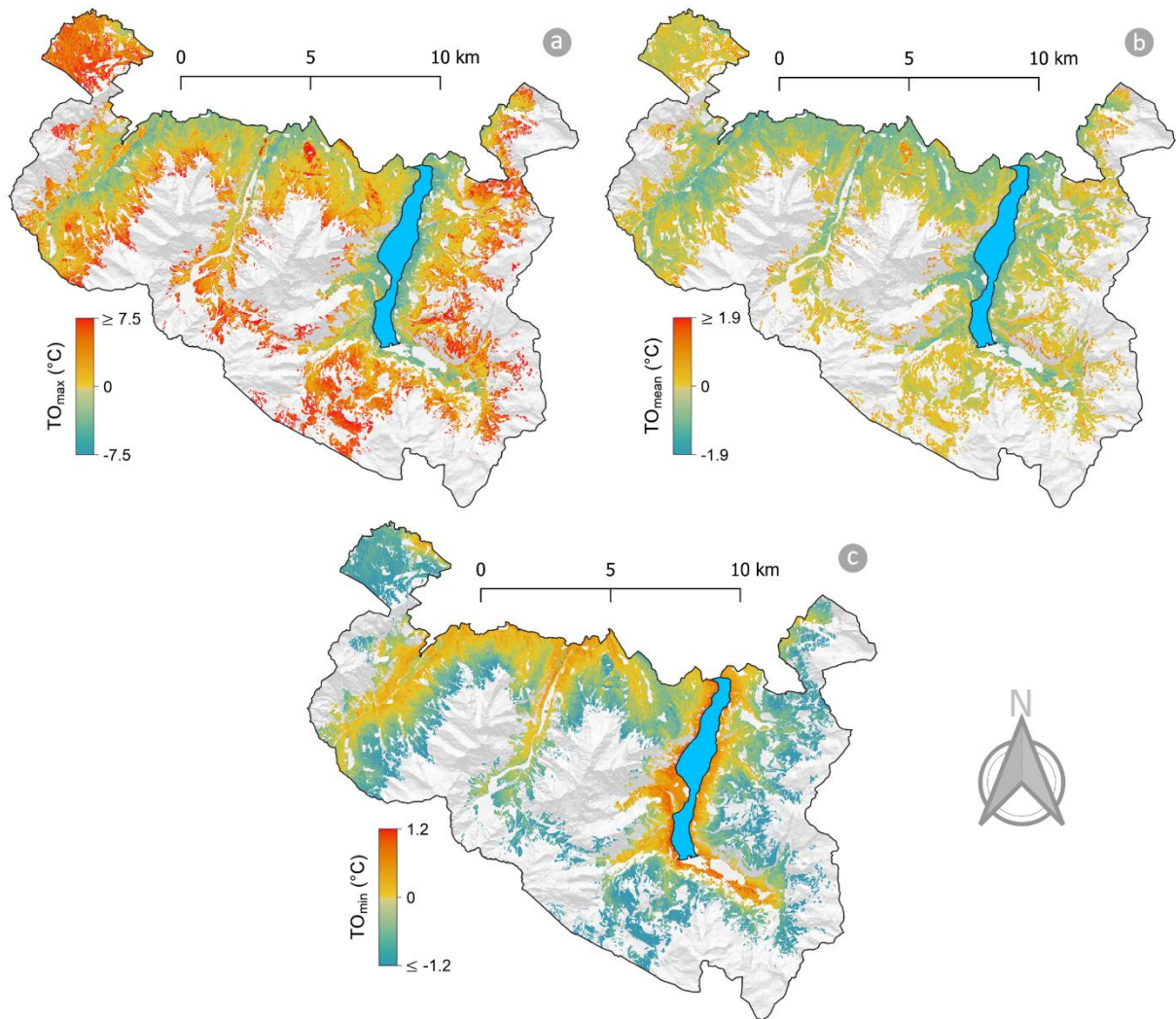
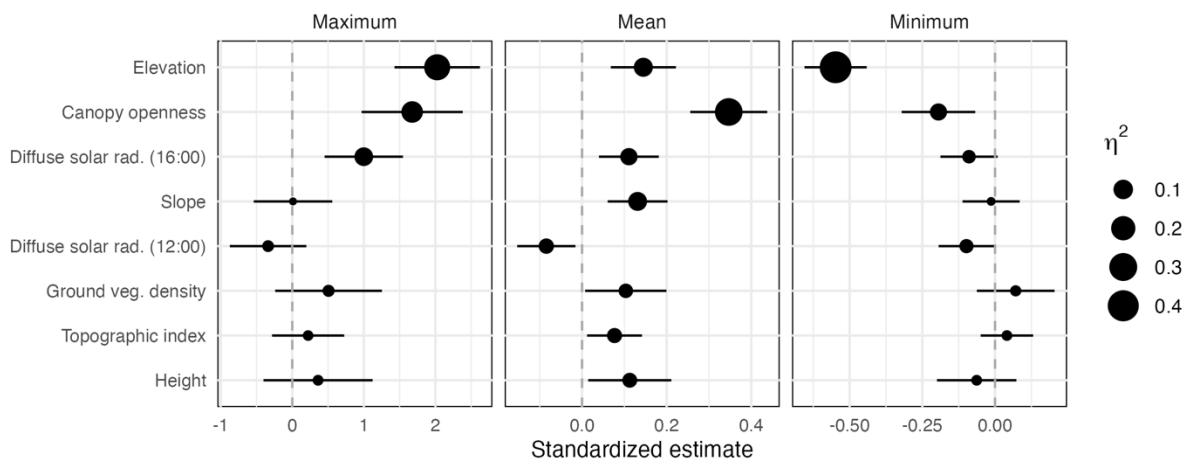


Figure 3: Maps of the maximum (a), the mean (b), and the minimum (c) of temperature offset for Berchtesgaden national park. For improved visualisation we centered the colour gradient and left out the ~1.2 % of the most extreme values.

Canopy openness and elevation were the two most important variables for predicting temperature offsets in our landscape, with higher importance of elevation for the extremes (minimum and maximum) but higher importance of openness for the mean offset (Figure 4). Canopy openness was positively correlated with maximum and mean temperature offset, but negatively correlated with minimum temperature offset. It explained 13.6%, 29.1% and 6.3% of the variance in the maximum, mean and minimum temperature offsets, respectively.

353 Ground vegetation density and canopy height did not have a measurable influence on
 1
 2 354 maximum and minimum temperature offsets, and only a weak positive association with mean
 3
 4 355 temperature offset. Besides elevation, which explained 24.6%, 9.1% and 42.7% of the variance
 5
 6 356 in maximum, mean and minimum temperature offsets, the influences of topographic effects
 7
 8
 9 357 were less clear. Diffuse incoming solar radiation at 16:00 correlated positively with the
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 11 358 maximum and mean offsets, whereas diffuse incoming solar radiation at 12:00 correlated
 12
 13 359 negatively with mean and minimum offsets. The topographic index had only a weak positive
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 15 360 correlation with mean temperature offset.

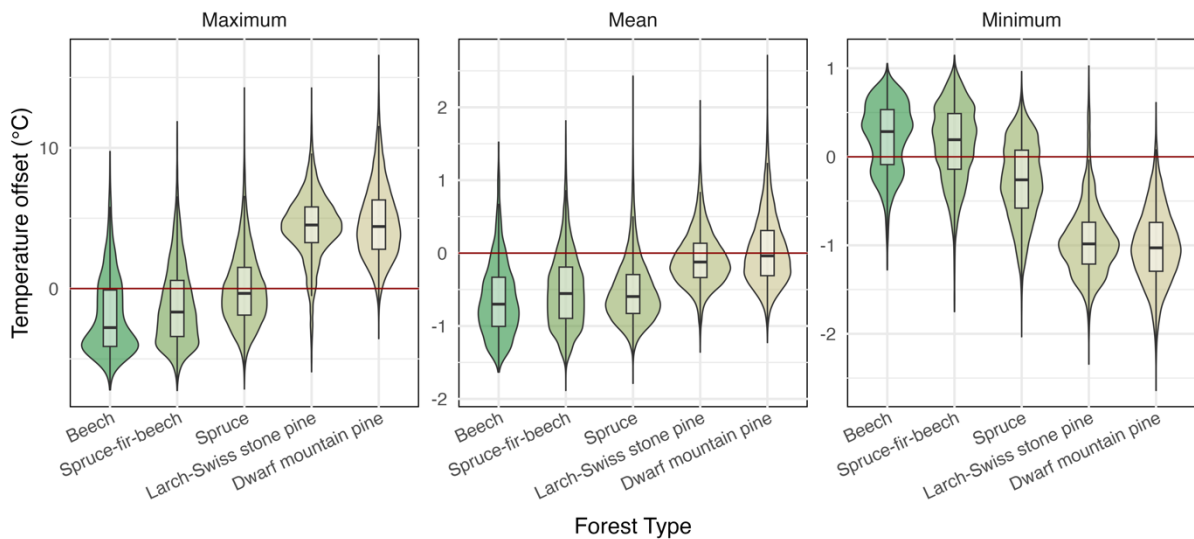


361
 362 **Figure 4:** Model coefficients with 95% confidence intervals (standardized estimate) and
 363 relative influence, measured in terms of partial η^2 values (the proportion of the total
 364 variance that is attributed to an individual predictor).

365 *Influence of forest type and disturbance on temperature offsets*

366 There was considerable variation in temperature offsets between – but also within – forest
 367 types (Figure 5). Beech forests – found mostly in submontane areas – had the lowest
 368 maximum and mean temperature offsets and the highest minimum temperature offsets.
 369 Nevertheless, beech forests also had a considerable fraction of forests with positive mean
 370 (11 %) and maximum (24 %) temperature offsets and negative minimum temperature offsets
 371 (30%). Spruce-fir-beech and spruce forests – which span a wide range of elevations – also
 372 showed high variability, with largely negative mean temperature offsets (84% and 89%,

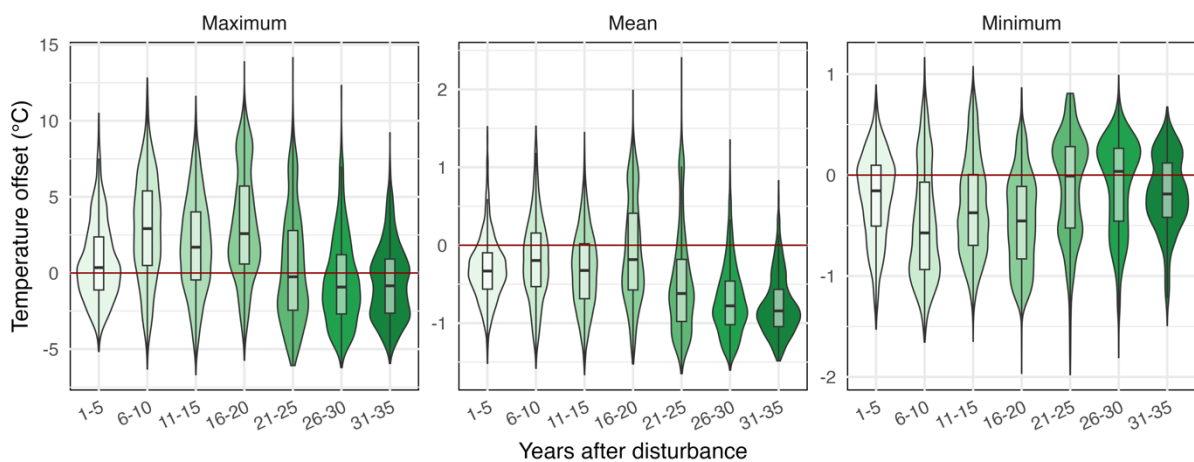
373 respectively), but more variable maximum temperature offsets (30% and 45% of spruce-fir-
 374 beech and spruce forests had positive maximum temperature offsets; Figure 5). Larch-Swiss
 375 stone pine and dwarf mountain pine forests showed overall mixed mean temperature offsets,
 376 with mostly warmer maximum temperatures and colder minimum temperatures within
 377 forests than in open lands. Overall, our results show that forest type is an important proxy
 378 of local forest microclimate, with forest type explaining 24% of the spatial variability in
 379 mean temperature offset and 45% and 46% of maximum and minimum temperature offsets
 380 (all for recently undisturbed forests).



381
 382 **Figure 5:** Distribution of maximum, mean and minimum temperature offsets across forest
 383 types. We only show forest cells without disturbance in the past 25 years. The red
 384 horizontal line shows where temperature offset is 0.

385
 386 Forest disturbances and subsequent post-disturbance forest development also had
 387 substantial influence on the variability in forest temperature offsets (Figure 5). While average
 388 temperature offsets stayed rather consistent over post-disturbance development, maximum
 389 temperature offset increased > 5 years after disturbance, whereas minimum temperature offset
 390 decreased. That is, between 6 and 20 years after disturbance, forests tend to have warmer
 391 maximum and cooler minimum temperatures compared to open lands. During canopy closure

392 (21-25 years after disturbance), both maximum and minimum temperature offsets shifted back
 393 towards negative/positive offset values. Overall, disturbance and post-disturbance recovery
 394 was an important driver of temperate offsets. In disturbed sites, time since disturbance
 395 explained 12% of the variance in maximum and mean temperate offsets and 6 % of minimum
 396 temperature offset. Across all forests, however, disturbances explained less than 2% of the
 397 spatial variation in temperature offsets.



398
 399 **Figure 6:** Distribution of maximum, mean and minimum temperature offsets over
 400 time since disturbance. The red horizontal line shows where temperature offset is 0.

402 Discussion

403 We here present an application of LiDAR data for mapping temperature offsets across a
 404 topographically complex landscape with more than 8,000 ha of forest area. Overall, we show
 405 that summer temperature offsets were highly variable, with both colder and warmer
 406 temperatures within forests compared to open lands. Canopy openness and a second-order
 407 polynomial term of elevation were the most important predictors of temperature offsets.

408 Canopy openness determines the amount of incoming solar radiation that reaches the forest
 409 floor and thus the direct energy available at the forest floor. The strong influence of canopy
 410 openness is in line with previous studies (De Frenne et al. 2021; Zellweger et al. 2019).

411 Elevation does not directly influence temperature offsets, but serves as proxy for climatic

1
2 413 and Hylander 2017). Elevation further serves as a proxy for turnover in forest composition
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4 414 and thus different temperature offsets we observed for the different forest types in our study
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6
7 415 landscape (Figure 5). Yet, by controlling for elevation in our model, we also show that even
8
9 416 within the same forest type (i.e., the same elevation zone) canopy density plays a crucial role
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11 417 for determining temperature offsets, highlighting the overall important role of the forest
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13
14 418 canopy in regulating microclimate. Local topography played only a minor role for
15
16 419 temperature offsets in our study, except for the potential solar radiation in the afternoon.
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18 420 Comparing our models to those of previous studies, e.g., of Haesen et al. (2021) and Davis et
19
20
21 421 al. (2019), revealed that the performance of our models in terms of R^2 was slightly lower.
22
23 422 However, important differences in study design make a direct comparison challenging:
24
25 423 Davis et al. (2019), modelled daily variation in absolute microclimatic temperature, and
26
27
28 424 Haesen et al. (2021) included additional predictors such as mean annual cloud cover and
29
30 425 long-term average macroclimatic conditions. Considering the high topographic complexity
31
32
33 426 and high variability in forest types in our landscape, it can be concluded that the
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35 427 performance of our models was overall satisfactory, and that LiDAR data is well suited for
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37 428 consistently predicting temperature offsets, even in topographically complex terrain.

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40 429 Average and maximum temperature offset predictions reported in our study tended to
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42 430 be low but within range of previous studies (De Frenne et al. 2019; Haesen et al. 2021). De
43
44 431 Frenne et al. (2019) reported temperature offsets to vary substantially within and among
45
46 432 biomes, with boreal biomes exhibiting lower offsets than temperate and tropical biomes. In
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48
49 433 terms of microclimatic buffering our conifer-dominated temperate mountain forests thus
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51 434 behave similarly to boreal forests. Our results also highlight that forests not always cool
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54 435 temperatures in summer, but that the influence of structure, composition and disturbance
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56 436 history can also lead to warmer microclimates compared to open lands. This might be
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58
59 437 especially true for mountain forests in high elevations close to the timber line, which are often
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61 438 open in structure and are generally underrepresented in continental-scale assessments of

439 microclimate (e.g., Haesen et al. 2021). We found that less than half of the forests in our
1
2 440 mountain landscape did, in fact, not buffer temperature extremes (i.e., positive maximum and
3
4 441 negative minimum offsets). While counterintuitive, the low or even reversed temperature
5
6 442 offsets found in our study are plausible and can be explained by at least two factors: First, the
7
8 443 difference in height of measurement between microclimate loggers and weather stations.
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10 444 Microclimate measurements were taken near the ground surface, which tends to be warmer
11
12 445 than air temperatures on summer days (García-García et al. 2019) and likely colder than air
13
14 446 temperatures during the night. Macroclimatic readings, on the other hand, were taken at a
15
16 447 minimum height of two meters above ground. The temperature offset metrics derived here
17
18 448 thus reflect the difference between air temperatures, which are widely used when assessing
19
20 449 the biotic response to climate change, and the microclimatic temperatures that forest dwelling
21
22 450 species experience at the forest floor (e.g., forest floor plants, ground-dwelling insects).
23
24 451 Second, in open forests such as the sub-alpine forests in our landscape, microclimate loggers
25
26 452 might be directly exposed to the sun. The temperature recorded at the loggers might thus be
27
28 453 influenced by relatively short periods of time with direct incoming solar radiation heating up
29
30 454 the logger (Maclean et al. 2021). The absolute temperature offsets found in our study
31
32 455 landscape thus need to be interpreted with caution. Future work should study temperatures
33
34 456 inside and outside of forests at comparable heights to isolate the effects of forest structure,
35
36 457 forest type and disturbance on microclimatic temperatures more stringently. Recoding
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38 458 additional climate parameters (i.e., humidity, incoming solar radiation and wind speed) might
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40 459 further aid the interpretation of the offsets recorded in our study.
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49 460 The observed influence of forest type on temperature offset was in line with our
50
51 461 expectations. Subalpine larch-Swiss stone pine and dwarf mountain pine forests had
52
53 462 considerably warmer maximum and mean temperatures as well as colder minimum
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55 463 temperatures compared to open lands, which are likely caused by a high abundance of
56
57 464 coniferous shrubs at the forest floor and sparse forest cover typical for subalpine forests. These
58
59 465 particular structures cause the forest floor to be exposed to high incoming solar irradiation
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466 and stronger outgoing longwave radiation, while the sparse tree cover still shields from wind.
1
2 467 This results in microclimates that have warmer maximum and colder minimum temperatures
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4 468 than open lands, as has already been reported in previous studies (von Arx, Dobbertin, and
5
6 469 Rebetez 2012; Renaud et al. 2011). The often shallow soils in sub-alpine forests might further
7
8 470 lead to low evaporative cooling in the summer, which can further contribute to the high
9
10 471 maximum temperatures in those systems reported in our study. Mountain forests are also
11
12 472 more complex in spatial configuration, with more openings and edges allowing solar radiation
13
14 473 to reach the forest floor even in closed canopy stands (Meeussen et al. 2021). In general, the
15
16 474 open forest structures leading to positive temperature offsets can be seen as an adaptation of
17
18 475 plants to the harsh conditions at the tree line, where plant life is mostly limited by low
19
20 476 temperatures (Körner 2012). In contrast, mostly closed canopy conditions with fewer
21
22 477 openings and edges are likely responsible for the generally cooler maximum temperatures and
23
24 478 warmer minimum temperatures found in beech, spruce, and spruce-fir-beech forests. Yet, we
25
26 479 observed significant variation within each group (Figure 4). This effect can partly result from
27
28 480 a decrease in canopy cover with increasing elevation even within the same forest type (Gómez-
29
30 481 Hernández et al. 2012; Ehbrecht et al. 2019; von Arx, Dobbertin, and Rebetez 2012).

31
32 482 The influence of disturbance on temperature offset largely supported our hypothesis,
33
34 483 with disturbances generally decreasing minimum temperatures and increasing maximum
35
36 484 temperatures in the short term, but microclimatic temperatures recover as the canopy closes.
37
38 485 After a high severity disturbance, large parts of the forest canopy are lost, leading to
39
40 486 temporarily open forest stands with an increased amount of solar radiation reaching the forest
41
42 487 floor (Hardwick et al. 2015; Jucker et al. 2018; Smith-Tripp et al. 2022; Thom et al. 2020).
43
44 488 Interestingly, the most positive maximum offset was found more than five years after
45
46 489 disturbances, which might be explained by more gradual disturbances typical for mountain
47
48 490 landscapes (interacting wind and bark beetle disturbances; Seidl and Rammer (2017); Stritih,
49
50 491 Seidl, and Senf (2023)). Further, residual structures, such as surviving trees, standing
51
52 492 deadwood and snags likely contribute to a complex thermal regime shortly after the

493 disturbance. We note, however, that there is also uncertainty in the attribution of the onset of
1
2 494 disturbance in the disturbance map used herein (Senf and Seidl 2021). Interestingly, the
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4 495 temperature offset values after disturbance were similar to those found in the subalpine zone,
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6
7 496 confirming the importance of forest structure and especially canopy openness in determining
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9 497 microclimates. Furthermore, our findings highlight the potential of forest disturbances to
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11 498 significantly alter microclimatic conditions in closed canopy forests. After disturbance, forests
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13
14 499 close their canopy in the course of forest development. The resultant reduction in solar
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16 500 irradiation causes temperature offsets to recover towards closed canopy conditions (Schwartz
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18 501 et al. 2022; Zenner et al. 2016). We here show that it takes up to two decades for temperature
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21 502 offsets to recover to values similar to closed canopy conditions, underlining that disturbances
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23 503 can have a long-lasting impact on the climate regulating function of forests.
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26 504

27 505 **Conclusion and outlook**

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30 506 We here present a novel approach for the landscape-scale mapping of microclimatic
31
32 507 temperature from airborne LiDAR data. Our results demonstrate the ability of LiDAR to
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34
35 508 capture forest structure and topographic features relevant for predicting microclimatic
36
37 509 conditions, even in a complex mountain landscapes. Given the growing availability of LiDAR
38
39
40 510 data, our approach can be readily applied to other regions where similar datasets are available.
41
42 511 Our results highlight the importance of forest structure – in particular canopy openness – for
43
44 512 microclimate regulation, and demonstrate that forest disturbances can significantly alter those
45
46
47 513 structures and thus microclimate for several decades. This finding has potential implications
48
49 514 for the future distribution of microrefugia under climate change, as the frequency and severity
50
51
52 515 of disturbances is likely to increase in the Alps under climate change (Thom, Rammer, and
53
54 516 Seidl 2017; Seidl et al. 2017; Albrich et al. 2022). Future research should therefore assess how
55
56 517 the interaction between climate-driven shifts in forest types and amplified disturbances
57
58
59 518 influences microclimate in mountain forests. The spatially explicit maps of temperature offsets
60
61 519 provided here can be used to improve the assessment of climate risks for biodiversity, i.e.,
62
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520 through incorporating microclimatic temperature offsets into species distribution models. A
1
2 521 better quantification of forest microclimate will allow for a more process-based understanding
3
4 522 of the effects of climate change on forest-dependent communities.
5
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7 523

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30 533

33 534 **Data availability**

35 535 All data and code created/used in this study are publicly available under
36
37 536 <https://doi.org/10.5281/zenodo.8163612>
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