

Northumbria Research Link

Citation: Maclean, Ilya M. D., Suggitt, Andrew, Wilson, Robert J., Duffy, James P. and Bennie, Jonathan J. (2017) Fine-scale climate change: modelling spatial variation in biologically meaningful rates of warming. *Global Change Biology*, 23 (1). pp. 256-268.
ISSN 1354-1013

Published by: Wiley-Blackwell

URL: <https://doi.org/10.1111/gcb.13343> <<https://doi.org/10.1111/gcb.13343>>

This version was downloaded from Northumbria Research Link:
<http://nrl.northumbria.ac.uk/id/eprint/40381/>

Northumbria University has developed Northumbria Research Link (NRL) to enable users to access the University's research output. Copyright © and moral rights for items on NRL are retained by the individual author(s) and/or other copyright owners. Single copies of full items can be reproduced, displayed or performed, and given to third parties in any format or medium for personal research or study, educational, or not-for-profit purposes without prior permission or charge, provided the authors, title and full bibliographic details are given, as well as a hyperlink and/or URL to the original metadata page. The content must not be changed in any way. Full items must not be sold commercially in any format or medium without formal permission of the copyright holder. The full policy is available online: <http://nrl.northumbria.ac.uk/policies.html>

This document may differ from the final, published version of the research and has been made available online in accordance with publisher policies. To read and/or cite from the published version of the research, please visit the publisher's website (a subscription may be required.)



**Northumbria
University**
NEWCASTLE



University**Library**

1 **Fine-scale climate change: modelling spatial variation in biologically meaningful rates**
2 **of warming**

3

4 Running title: *Fine-scale spatial variation in warming*

5

6 Ilya M.D. Maclean^{1*}, Andrew J. Suggitt¹, Robert J. Wilson², James P. Duffy¹ and Jonathan J.
7 Bennie¹

8

9 ¹Environment and Sustainability Institute, University of Exeter Cornwall Campus, TR10
10 9FE, United Kingdom.

11 ²College of Life and Environmental Sciences, University of Exeter, Exeter, EX4 4PS, United
12 Kingdom.

13

14 *Correspondence: Ilya M. D. Maclean, tel: +44 (0)1326 255 968, e-mail:
15 *i.m.d.maclean@exeter.ac.uk*

16

17 Key words: climate change, microrefugia, cryptic refugia, microclimate, topoclimate, species
18 distributions, landscape.

19

20 Type of paper: primary research article.

21 **Abstract**

22 The existence of fine-grain climate heterogeneity has prompted suggestions that species may
23 be able to survive future climate change in pockets of suitable microclimate, termed
24 ‘microrefugia’. However, evidence for microrefugia is hindered by lack of understanding of
25 how rates of warming vary across a landscape. Here we present a model that is applied to
26 provide fine-grained, multi-decadal estimates of temperature change based on the underlying
27 physical processes that influence microclimate. Weather station and remotely-derived
28 environmental data were used to construct physical variables that capture the effects of
29 terrain, sea-surface temperatures, altitude and surface albedo on local temperatures, which
30 were then calibrated statistically to derive gridded estimates of temperature. We apply the
31 model to the Lizard Peninsula, United Kingdom to provide accurate (mean error = 1.21°C;
32 RMS error = 1.63°C) hourly estimates of temperature at a resolution of 100 m for the period
33 1977 to 2014. We show that rates of warming vary across a landscape primarily due to long-
34 term trends in weather conditions. Total warming varied from 0.87 to 1.16°C, with the
35 slowest rates of warming evident on north-east-facing slopes. This variation contributed to
36 substantial spatial heterogeneity in trends in bioclimatic variables: for example, the change in
37 the length of the frost-free season varied from +11 to -54 days and the increase annual
38 growing degree-days from 51 to 267 °C days. Spatial variation in warming was caused
39 primarily by a decrease in daytime cloud cover with a resulting increase in received solar
40 radiation, and secondarily by a decrease in the strength of westerly winds, which has
41 amplified the effects on temperature of solar radiation on west-facing slopes. We emphasise
42 the importance of multi-decadal trends in weather conditions in determining spatial variation
43 in rates of warming, suggesting that locations experiencing least warming may not remain
44 consistent under future climate change.

45

46 **Introduction**

47 Biodiversity conservation and environmental management increasingly depend on our ability
48 to understand and predict the responses of species and ecological communities to climatic
49 change. To date, however, most predictions for the effects of climatic change on biodiversity
50 have been derived using grid cell resolutions that are three to four orders of magnitude
51 coarser than the size of the focal species being studied (Potter *et al.*, 2013). Wind patterns and
52 landscape features such as local terrain, vegetation and soil properties interact with regional
53 climate to create complex mosaics of temperature and water availability (Dobrowski, 2011,
54 Hannah *et al.*, 2014, Maclean *et al.*, 2012, Suggitt *et al.*, 2011). This fine-grained variation in
55 climate strongly influences species' distributions (Lassueur *et al.*, 2006, Randin *et al.*, 2009,
56 Scherrer & Körner, 2011, Sebastiá, 2004) and their predicted responses to future climatic
57 change (Franklin *et al.*, 2013, Gillingham *et al.*, 2012).

58

59 The existence of fine-grain heterogeneity has prompted suggestions that species may be able
60 to survive future climatic change by exploiting pockets of suitable microclimate, often termed
61 'microrefugia' (Hannah *et al.*, 2014, Rull, 2009). The term 'microrefugia' is borrowed from
62 paleoecology and is usually used to describe locations with unusual microclimate in which
63 isolated populations survive unsuitable regional climate (Rull, 2009). After the Last Glacial
64 Maximum, many species recolonized parts of their historic range at rates much faster than
65 predicted from dispersal models (Clark *et al.*, 1998). While long-distance dispersal may be
66 important in explaining this phenomenon (Phillips *et al.*, 2008), an alternative explanation is
67 that species recolonized from localities with suitable microclimate much closer to their
68 former range (Stewart & Lister, 2001). Nonetheless, the possible existence of microrefugia is
69 still widely debated (Hylander *et al.*, 2015, Tzedakis *et al.*, 2013) and empirical evidence for

70 the existence of microrefugia, particularly in the context of recent and ongoing climatic
71 change, is still remarkably scarce (Suggitt *et al.*, 2014).

72

73 It is sometimes argued that the existence of fine-grained heterogeneity in itself will buffer
74 species against the effects of climatic change (e.g. Willis & Bagwhat 2009). However, many
75 species are already restricted to specific microclimates, and if warming microclimates at the
76 trailing edge of species' ranges are vacated at the same rate as sites become newly occupied
77 at the leading edge, then the effects of microclimate variation will "average out" (Bennie *et*
78 *al.*, 2014). A further consideration of whether or not microclimates buffer the effects on
79 species of regional climate warming is whether or not all parts of the landscape are
80 undergoing climatic change at the same rate. To date, however, the extent to which rates of
81 change in local climate are decoupled from regional climate has received little attention from
82 biologists, in spite of its importance as a mechanism for explaining how species are able to
83 persist in microrefugia (though see Pepin *et al.* 2011 and Pike *et al.* 2013 for examples in the
84 climate literature). A possible reason for this is that it is difficult to quantify fine-grained
85 variation in rates of climatic change, because this requires climate to be modelled or
86 measured both: a) over a sufficiently long time period to encompass an appreciable level of
87 global warming, and b) at a sufficiently fine resolution to quantify local variation in rates of
88 change.

89

90 While next-generation fine-grained climate models are emerging, our understanding of local
91 variation in rates of change remains limited. Kearney *et al.* (2014) present a mechanistic
92 model of gridded hourly estimates based on local modifiers of the solar radiation budget for
93 the period 1961 to 1990, but the grid cell resolution of this model is a relatively coarse 15 km
94 and local variation in rates of change is not explored. Dobrowski (2011) identifies terrain

95 features that are likely to be effectively decoupled from regional climatic patterns, but stops
96 short of explicitly modelling the effects of these features over an extended time period.
97 Gunton *et al.*, (2015) model local ground temperatures across Europe, but do not provide
98 long-term estimates of change. Likewise Bennie *et al.* (2008), using similar principles,
99 modelled near-surface temperatures at resolutions of one metre, but again do not assess local
100 variation in long-term change. Heterogeneity in long-term warming was assessed in a study
101 by Ashcroft *et al.*, (2009) in which rates of warming between 1972 and 2007 were modelled
102 within a 10 km x 10 km region approximately 80 km south of Sydney, Australia. However,
103 long-term estimates of temperature change in this study and determinants of local variation in
104 change are estimated using a phenomenological approach based on statistical relationships
105 established over a relatively short period. Models based on phenomenological descriptions
106 can be unreliable when used to predict beyond the realm of existing data (e.g. Rice, 2004).
107 While models based on the physical processes can be difficult to parameterise and necessitate
108 assumptions to be made about model structure, they are often more likely to provide reliable
109 predictions under novel conditions (Evans, 2012).

110

111 Here we present a model that incorporates the important mechanistic processes that govern
112 variation in climate to provide fine-grained (100 m) hourly estimates of temperature over
113 decades at regional scales. The model is applied to assess spatial variation in rates of
114 warming and changes in biologically meaningful derivatives of temperature between 1977
115 and 2014 across a 20 x 30 km region located on the southwest coast of Britain (The Lizard
116 Peninsula in Cornwall). While all parts of the landscape warmed during this period, rates of
117 warming differed by a factor of 1.3, with significantly slower rates of mean warming evident
118 on north-east-facing slopes and valley bottoms. This spatial variation in temperature change
119 has led to even greater spatial variation in the rate at which bioclimatic variables have altered,

120 with the overall change in the length of the frost free growing season, for example, varying
121 from a decrease of 11 days to an increase of 54 days. We provide insight into the mechanisms
122 governing rates of warming, demonstrating how landscape features interact with changing
123 weather patterns to decouple local changes in climate from regional averages.

124

125 **Materials and methods**

126 *Overview of approach*

127 The study was conducted on the Lizard Peninsula ($50^{\circ} 2'N$, $5^{\circ} 10'W$), a Special Area for
128 Conservation (92/43/EEC) located on the most southerly point of Britain (Fig. 1). The
129 climate has a strong maritime influence with mild winters and low annual temperature range.
130 The site is surrounded on three sides by the sea, has an elevation range of 0 to 185 metres
131 above sea level and comprises a mosaic of grassland, woodland and heath on a variety of
132 slopes and aspects. We model hourly local temperature anomalies from a standard
133 meteorological station as a function of landscape features that interact with physical
134 determinants of local temperatures. Estimates are for one metre above the ground at a grid
135 cell resolution of 100 m for the period 1st January 1977 to 31st December 2014.

136

137 To drive the model, hourly weather data for the period 1st January 1977 to 31st December
138 2014 were obtained for Culdrose weather station (Fig. 1). A small number (<0.01%) of
139 observations were missing and were imputed by fitting a cubic spline using the Forsyth *et al.*
140 (1977) method implemented by the spline function in R (R Development Core Team, 2013).
141 Five groups of factors were considered to influence local temperatures, details of which are
142 provided below: (i) coastal influences, as a function of sea surface temperatures, wind speed
143 and direction and sea-exposure; (ii) the local radiation balance, as a function of weather
144 conditions, surface albedo, slope and aspect; (iii) altitudinal effects, as function of elevation

145 and humidity; (iv) latent heat exchange, as function of evapotranspiration and condensation;
146 and (v) cold air drainage into valley bottoms, as a function of flow accumulation potential
147 and weather conditions that lead to katabatic flow.

148

149 To calibrate the model, 35 iButton temperature dataloggers were deployed in open,
150 unwooded areas across the Lizard Peninsula between 1st March 2010 and 14th December
151 2011, and set to record temperatures at hourly intervals. Loggers were placed to capture
152 spatial gradients in the main determinants of climate and provided 89,250 measurements of
153 temperature for model calibration. Each logger recorded temperature with a specified
154 accuracy of $\pm 0.5^{\circ}\text{C}$, and 0.0625°C resolution. Loggers were attached to a wooden pole
155 one metre above the ground and orientated to face north and shielded from direct sunlight
156 using a white plastic screen. To provide an independent validation of the model results, an
157 additional 30 loggers were deployed between March and November 2014 at nearby, but not
158 identical locations to those deployed in 2010-11 (mean distance between pairs of locations:
159 381 m; Fig. 1).

160

161 To improve readability, we omit mathematical details of our methods from the main text.
162 Further details and functions for implementing individual components of the model, written
163 using R statistical software (R Development Core Team, 2013), are provided in supporting
164 information (Appendix S1 and S2). However, an overview of the underlying rationale and a
165 synopsis of our approach are provided below.

166

167 *Coastal influences*

168 We obtained a one degree gridded dataset of monthly sea ice and sea surface temperatures
169 from the Met Office Hadley Centre (Rayner *et al.*, 2003) and extracted data for the four grid

170 cells corresponding to the region 49-51°N and 4-6°W. We resampled these datasets at 100m
171 grid cell resolution using bilinear interpolation and projecting them onto the Ordnance Survey
172 equal area grid (OSGB36). We then calculated the mean sea surface temperature for the
173 marine portion of our entire study area. We obtained hourly values by simple linear
174 interpolation, assuming that the mean value for each month corresponded to the mid-point of
175 that month. Due to the high specific heat capacity of water, sea surface temperatures undergo
176 only minor high frequency fluctuations (Stacey & Davis, 1977), so simple interpolation was
177 deemed a reasonable approximation.

178

179 To capture the influence of sea temperatures on local temperatures, which is itself affected by
180 wind direction (Haugen & Brown, 1980), we calculated the proportion of 100 m x 100 m
181 pixels that were land as opposed to sea upwind of each focal pixel in each of 36 different
182 compass directions (0°, 10°...350°) using a 100 m resolution gridded dataset of land and sea.
183 We then weighted these proportions by the inverse of the distance to the coast, to ensure that
184 coastal grid cells were attributed a higher coastal exposure influence (function *inv.ls* in
185 Appendix S1). Coastal effects on local temperatures are also influenced strongly by wind
186 speed (Haugen & Brown, 1980). However, surface friction tends to reduce airflow, and wind
187 speeds at one metre height differ from those measured at the height of the Culdrose
188 anemometer (33 m above the ground). To adjust for height, and derive estimates for one
189 metre above the ground, a logarithmic wind speed profile was assumed (Allen *et al.*, 1998;
190 function *wind.hgt* in Appendix S1). The sheltering effect of local topography was accounted
191 for by computing the shelter coefficient described by Ryan (1977; function *windcoef* in
192 Appendix S1).

193

194 *Solar radiation*

195 Local temperature anomalies due to variation in solar radiation approximate a linear function
196 of the net radiation flux at a location, with the slope of this relationship determined by local
197 wind speed (Bennie *et al.*, 2008). Net radiation is determined by the balance of short- and
198 long-wave radiation and surface albedo. We estimated surface albedo from 25 cm resolution
199 visual and 50 cm colour-infrared aerial photographs obtained from Bluesky (Bluesky
200 International Ltd, Coalville, UK). We weighted the reflectance value in each band by the
201 expected proportion of total solar energy contributed by each band by assuming that the
202 relationship between energy and wave-length approximates the 5250°C blackbody spectrum
203 described by Planck's law (function *albedo* in Appendix S1). This ignores temporally
204 variable, but relatively minor discrepancies caused by atmospheric absorption of specific
205 wavelengths. The mean value in each 100 m grid cell was calculated.

206

207 Satellite-derived estimates of direct and diffuse shortwave radiation are available at hourly
208 intervals at a horizontal grid cell resolution of 0.03° from the Satellite Application Facility on
209 Climate Monitoring (Posselt *et al.*, 2011). However, as they do not span the duration of our
210 study, we developed a model for predicting solar radiation from meteorological station
211 estimates of cloud cover (recorded in oktas). First we obtained satellite-derived estimates of
212 radiation for the grid cell corresponding to the location of Culdrose weather station for every
213 hour in 2005 (the year with fewest missing weather station observations). Then, because solar
214 irradiance is affected by solar azimuth and zenith, we computed the proportion of potential
215 direct irradiance intercepted by a flat surface located at Culdrose (hereafter referred to as the
216 solar coefficient) for every hour using the methods outlined in Hofierka & Šúri (2002;
217 function *solarindex* in Appendix S1). Second, because solar energy is attenuated more by
218 clouds when the sun is low above the horizon, we calculated the airmass coefficient for every
219 hour in 2005. The airmass coefficient is the direct optical path length of a solar beam through

220 the Earth's atmosphere, expressed as a ratio relative to the path length vertically upwards. To
221 account for the earth's curvature, we used the method by Kasten and Young (1989) in which
222 the air mass coefficient can be derived from the solar zenith (function *airmasscoef* in
223 Appendix S1). Next, to estimate the effects of cloud cover on full beam solar irradiance, we
224 divided each satellite-derived estimate of direct and diffuse solar irradiance by the solar
225 coefficient. As direct irradiance is affected both by cloud cover and the airmass coefficient,
226 we fitted a linear model with the full beam estimates of direct irradiance as a dependent
227 variable, and airmass coefficient, cloud cover and an interaction between cloud cover and the
228 airmass coefficient as predictor variables. To reduce heteroscedasticity, we performed square-
229 root transforms on cloud cover and full-beam irradiance and a logarithmic transform on the
230 airmass coefficient. As diffuse irradiance is highest with intermediate levels of cloud cover,
231 we fitted a linear model with diffuse radiation as the dependent variable and just cloud cover
232 and the square of cloud cover as predictor variables. Again to reduce heteroscedascity, we
233 square-root transformed scaled solar irradiance. Coefficient estimates of these models were
234 used to derive hourly estimates of full beam solar irradiance and diffuse radiation for the
235 entire duration of our study.

236

237 Slope, aspect and topographic shading influence strongly the amount of radiation intercepted
238 by a surface and act as one of the dominant influences on local temperatures (Bennie *et al.*
239 2008). To account for the effects of local terrain on direct radiation, we calculated the solar
240 coefficient for an inclined surface using the method detailed in Bennie *et al.* (2008; function
241 *solarindex* in Appendix S1) and multiplied our coarse-grained cloud-cover derived estimates
242 of full beam radiation by this coefficient. Topographic shading is also accounted for when
243 implementing this method by assuming that a surface receives no direct radiation when the
244 sun is below the local horizon. Slope, aspect and horizon angles were derived from a 5 m

245 resolution digital terrain model obtained from Bluesky (Bluesky International Ltd, Coalville,
246 UK) coarsened to 100 m resolution by computing mean values within each grid cell. Local
247 topographic effects on diffuse radiation were calculated by scaling our cloud-cover derived
248 estimates of diffuse radiation by the proportion of sky in view, using methods described in
249 Hofierka & Šúri (2002; function *skyview* in Appendix S1).

250

251 Net long-wave radiation was calculated from temperature and relative humidity data using
252 the method described in Allen *et al.* (1998; functions *netlong* in Appendix S1). Using this
253 approach, the effects of cloudiness are accounted for by estimating the ratio of net shortwave
254 to clear sky shortwave radiation, which in our model was estimated directly from cloud
255 cover. Longwave radiation was assumed to be uniform across the landscape and hence the
256 meteorological station temperature was used.

257

258 *Altitudinal effects*

259 We assumed a simple dry adiabatic lapse rate such that temperature declines with altitude at a
260 standard dry adiabatic lapse rate of 9.8°C per 1000 m, but accounted for shallower
261 temperature-altitude gradients under saturated conditions by explicitly calculating latent heat
262 exchange (see below), resulting in typical adiabatic lapse rates of 4 to 6°C per 1000 m.
263 Differences in altitude between the standard meteorological station and each location were
264 calculated from digital elevation data.

265

266 *Latent heat exchange*

267 Condensation releases latent heat energy warming local air temperatures by as much as 2°C
268 (Geiger, 1965). Conversely, evapotranspiration uses latent heat energy, cooling local
269 temperatures. Localised variation in these can result in small, but important variations in

temperature. As calculation of condensation and evapotranspiration relies on knowledge of local temperatures, but in this instance is also used to derive local temperatures, we used the local temperature anomaly (i.e. the difference between modelled local temperature and that at the meteorological station) in the previous time step, to derive estimates of local differences in latent heat exchange from our reference meteorological station. We assume condensation occurs when drops in temperature result in relative humidity exceeding 100%. First, from Allen *et al.* (1998) we calculate the local relative humidity as a function of the relative humidity measured at the met station, saturated vapour pressure and absolute humidity, which is assumed to remain constant, thus allowing local relative humidity to exceed 100% (function *rh.change* in Appendix S1). Where local relative humidity is less than 100%, condensation is assumed not to occur, but where relative humidity would exceed 100% as a result of temperature decreases, the surplus water is assumed to condense (function *water.conden* in Appendix S1). Following Allen *et al.* (1998) potential evapotranspiration was calculated as a function of net radiation, local temperatures (estimated from anomalies in the previous time step), relative humidity, atmospheric pressure and wind speed using the Penman-Monteith equation (function *CRE* in Appendix S1).

286

287 *Cold-air drainage*

288 Under clear sky conditions with low wind speed, katabatic flow occurs, such that cold air
289 drains into valley bottoms (Dobrowski, 2011). Two components of cold air drainage were
290 considered. First we modelled the potential for different parts of the land surface to receive
291 cold air by calculating accumulated flow to each cell, as determined by accumulating the
292 weight for all cells that flow into each downslope cell, using the hydrological tools in ArcGIS
293 10.2 (ESRI, Redlands). We then identified the synoptic weather conditions under which cold
294 air drainage is likely. Following McGregor & Bamzelis (1995), we first collated and/or

calculated the following meteorological variables from the meteorological station data, aggregating data into 24-hour averages: (i) cloud cover (oktas), (ii) mean temperature ($^{\circ}\text{C}$), (iii) diurnal temperature range ($^{\circ}\text{C}$), (iv) surface atmospheric pressure (hPa), (v) relative humidity (%), (vi) wet bulb temperature ($^{\circ}\text{C}$), (vii) the dew point temperature ($^{\circ}\text{C}$), (viii) visibility (km), (ix) net radiation ($\text{MJ m}^{-2} \text{ hr}^{-1}$), (x) the westerly wind component (m s^{-1}) and (xi) the southerly wind component (m s^{-1}). Visibility data were log-transformed to reduce heteroscedasticity and all variables were z-score standardised. Meteorological variables were also de-seasoned by applying a 15 day running mean filter. Second, as the resulting variables were highly correlated with one another, we performed principal components analysis (PCA). To determine how many components to retain, we produced a scree plot, retaining four components which together explained 85% of the variance in the original data. Finally we performed Bayesian model-based clustering on these data using the R package mclust (Fritsch & Ickstadt, 2009), to group our data into distinct synoptic weather types. Using this approach, prior cluster partitions are identified using hierarchical agglomeration, and then Bayesian expectation-maximization is performed to automatically identify the final cluster number and membership thereof. Seven was considered the most likely number of distinct synoptic weather types using this method (see results). The synoptic weather type characterised by clear sky, high pressure, a high diurnal temperature range, good visibility and low relative humidity was considered to be the conditions under which temperature inversions occur (see e.g. Barr & Orgill, 1989). Temperature inversions were set to occur at night only as daytime cold air drainage into valleys is highly unusual in maritime climates (Gustavsson *et al.*, 1998).

317

318 *Model calibration*

319 Temperature anomalies were modelled using standard linear regression as a function of the
320 following sets of terms:

321

322 Radiation effects: $R_{net} + u_1 + u_1 R_{net}$

323 Coastal influences: $u_i L + u_1 L + LT_s$

324 Altitudinal effects: ΔT_a

325 Latent heat exchange: $E + C + W$

326 Cold air drainage: $I_c F$

327

328 Where R_{net} is net radiation, u_1 is wind speed one metre above the ground, u_i is the inverse of
329 wind speed given by $1/(u_1^{0.5}+1)$, L is the inverse distance-weighted measure upwind land-to-
330 sea ratio at Culdrose minus that at the site, T_s is sea-surface temperature minus that at
331 Culdrose, ΔT_a is the expected difference in temperature due to altitude, E is
332 evapotranspiration at Culdrose minus that at the site, C is condensation at Culdrose minus that
333 at the site, W is the change in lapse rate due to water condensation, F is accumulated flow
334 and I_c is a categorical variable set at one when temperature inversions exist, and 0 when
335 temperature inversion conditions do not exist. The terms are listed in anticipated descending
336 order of importance.

337

338 To fit the model, we sequentially added each set of terms to linear models and assessed
339 whether their inclusion improved model parsimony by computing the Akaike Information
340 Criterion (AIC). To reduce the effects of temporal autocorrelation, we randomly selected
341 2000 of the 89,250 logger-derived local temperature data and repeated the analyses 9999
342 times, computing AICs and coefficient estimates for each model run. To test the effects of
343 sample size on the retention of model terms, we repeated analyses varying the number of

344 randomly selected data points. To assess the sensitivity of our model selection to the
345 sequential adding of terms, we also fitted models with all possible combinations of terms, but
346 due to computational constraints, did this for 999 model runs only.

347

348 *Running and testing the model*

349 To run the model, median model coefficient estimates were used. The model was run in
350 hourly time steps for the period 1st January 1977 to 31st December 2014, deriving temperature
351 estimates for each 100 m grid cell of our study area. To test the model, model predictions
352 were compared with the observed data obtained through the deployment of temperature
353 loggers in 2014. To assess the relative contribution of individual components of the model,
354 we re-ran the model with only the set of coefficients with each effect included, holding other
355 coefficients at their mean. The model was coded and deployed in R statistical software (R
356 Development Core Team 2015) using a 2032 CPU Core Beowulf cluster.

357

358 *Spatial variation in climatic change*

359 To examine spatial variation in rates of warming, we calculated the overall degree of
360 temperature change in each grid cell using linear regression on hourly values over (a) the
361 entire duration of our study and (b) for 2010 to 2014, a period in which land temperature rose
362 much faster than sea temperatures. To examine how spatial variation in temperature change
363 manifests itself in changes to bioclimatic variables, we calculated the overall 1977-2014
364 change in (i) exposure to high temperatures, (ii) the number of growing degree-days, (iii) the
365 length of the frost-free season, (iv) diurnal temperature ranges, (v) isothermality, (vi)
366 temperature seasonality, (vii) maximum annual temperatures, (viii) minimum annual
367 temperatures, (ix) annual variations in temperature and (x-xiii) mean temperatures in the
368 warmest, coldest, driest and wettest quarter of each year. Exposure to high temperatures was

369 expressed as the number of hours in which temperatures equalled or exceeded 20°C, growing
370 degree-days were calculated as the difference between mean daily temperatures and a base
371 temperature of 10°C, with temperatures capped at 30°C and values summed for each year, and
372 the frost free season is the number of days between the last day in spring in which air
373 temperatures drop below zero and the first such day in autumn, with spring frost set at 1st of
374 Jan and autumn frost at 31st Dec in instances when temperatures did not drop below zero. The
375 diurnal temperature range was calculated as the difference between the maximum and
376 minimum hourly temperature in any given 24-hour period, the annual temperature range as
377 the difference between the maximum and minimum temperatures in any given year and
378 isothermality as the mean diurnal range divided by the annual temperature range. The
379 temperature seasonality was expressed as the standard deviation of temperatures expressed as
380 a percentage of the mean of those temperatures, with temperatures expressed in Kelvin
381 (Hijmans *et al.*, 2005). A quarter is here defined as any 90 day period. Temperature data from
382 the Culdrose weather station were used to calculate the warmest and coldest periods, and 5km
383 grid daily rainfall data available from the UK Met Office used to calculate the wettest and
384 driest periods. In each case, values were calculated separately for each year and linear-
385 regression on yearly values used to calculate the overall change. To gain insight into the
386 factors affecting warming, we reran the model calculating the separate contribution of each of
387 the five groups of factors to produce hourly temperatures. This was achieved by fitting the
388 model using only coefficients associated with each group of terms, holding all other terms
389 constant at their mean value. Long-term trend in selected weather variables (wind speed and
390 direction, cloud cover and the prevalence of each synoptic weather type) were also calculated
391 using linear-regression.

392

393 **Results**

394 *Model performance*

395 Our cloud-cover derived model provided good approximations of direct (Mean error = 34.9
396 Wm^{-2} ; RMS error = 71.8 Wm^{-2}), diffuse (mean error = 21.1 Wm^{-2} ; RMS error = 39.5 Wm^{-2})
397 and total solar irradiance (Mean error = 38.6 Wm^{-2} ; RMS error = 74.6 Wm^{-2}). Full results are
398 presented in supporting information (Appendix S3).

399

400 Our cluster analysis of weather variables identified seven synoptic weather types, one of
401 which represents conditions where no clear pattern could be discerned (Table S1 in Appendix
402 S3). Box and whisker plots indicating the median and range in meteorological variables
403 associated with each weather type and UK Met Office synoptic charts for dates conforming to
404 each synoptic weather type are shown in Appendix S3.

405

406 The most parsimonious model was that which included all terms. This model explained on
407 average 78% of the variation in local temperature anomalies ($r^2 = 0.711$ to 0.831), with a
408 mean error of 1.21°C and RMS error of 1.63°C . Parameter estimates, their standard deviation
409 and partial r-squared values are shown in Table 1. Comparisons between modelled hourly
410 predictions of temperature and recorded temperatures at two sites with divergent local
411 climatic conditions are shown in Figure 2. Further details of model performance are shown in
412 Appendix S3.

413

414 *Changes in weather variables*

415 Linear regression of hourly temperatures recorded at Culdrose weather station revealed an
416 increase of 0.94°C between 1977 and 2014 (95% CI = 0.89 to 0.99, n = 333096; Fig. 3a).
417 Over the same period, linear regression of monthly sea-surface temperatures showed an
418 overall increase of 0.89°C (95% CI = 0.21 to 1.57, n = 649; Fig. 3b). Among other weather

variables, there were two notable trends. First, linear regression on hourly estimates reveals that although cloud cover has changed little (<0.2%) over the duration of the study (95% CI = -0.49% to 0.15%, n = 333096), daytime cloud cover decreased by 4.0% (95% CI = -5.1% to -2.9%, n = 166602; Fig. 3c), whereas night-time cloud cover increased by 1.2% (95% CI = 0.7% to 1.7%, n = 166602; Fig. 3d). Changes in cloud cover appear to have manifested themselves in moderate increases in received solar radiation: direct radiation was estimated to have increased by 11.9 Wm^{-2} over the period of the study (95% CI = 5.2 to 18.7, n = 333096; Fig. 3e). However, diffuse radiation has changed little (95% CI = -2.8 to 7.0 Wm^{-2} , n = 333096; Fig. 3f).

428

Second, there appears to have been a shift in wind vectors. Linear regression of hourly values reveals a decrease in zonal (west to east) wind velocity of 0.66 ms^{-1} over the duration of the study (n = 333096, 95% CI = -0.71 to -0.60; Fig. 3g) and a decrease in meridional wind velocity (the northerly wind component) of 0.44 ms^{-1} (n = 333096, 95% CI = -0.49 to -0.39; Fig. 3h). Somewhat paradoxically, however, the synoptic weather type associated with easterly winds, weather type 1, also indicative of weakly anticyclonic conditions, high pressure and high relative humidity, decreased by 2.2% from 10.1% to 8.0% (n=38, 95% CI = -4.3 to -1.3%) and was the only type for which a trend was evident (Fig S6). The most likely explanation of this is that while the mean zonal component of the wind vector in any given year remained relatively constant over time during periods in which synoptic weather type 1 prevailed (95% CI = -0.93 to 1.01 ms^{-1} , n=38), the zonal component in any given year during periods in which synoptic weather types other than type 1 prevailed, decreased substantially (-1.75 ms^{-1} over the duration of the study; 95% CI = -1.41 to -2.09 ms^{-1} , n=38).

442

443

444 *Spatial variation in climatic change*

445 Linear regression of hourly temperatures in each grid cell demonstrated that grid cells have
446 warmed, but rates of warming between 1977 and 2014 varied from 0.87°C to 1.16°C, with
447 two dominant patterns evident (Fig. 4a). First, grid cells receiving high solar radiation have,
448 on average warmed by more than those receiving low radiation. Second, east-facing slopes,
449 particularly those exposed to the sea have warmed the least. The period 2010 to 2014, in
450 which temperatures recorded at Cudrose rose by 2.30 °C in comparison to sea-surface
451 temperatures rising by 1.34 °C (Fig. 3a,b), reveals broadly similar patterns, although an east-
452 west gradient is more evident, with the highest temperature increases occurring towards the
453 west of our study area (Fig. 4b).

454

455 Temperature increases were higher in the cold-season (22nd Dec-21st Mar) than in the warm-
456 (18th Jun-15th Sep) and dry-season (14th Mar to 12th Jun), but were least marked in the wet-
457 season (5th Oct-2nd Jan), implying that it is late-winter temperatures that have risen the most
458 (Appendix S4g-j). Spatial patterns of change in bioclimatic variables (e.g. Appendix S4a-f)
459 highlight that even moderate variations in temperature increase can lead to marked variation
460 in biologically meaningful climate variables. The overall change in the number of hours of
461 exposure to high temperatures (>20°C) varied from a decrease of 15 hours to an increase of
462 256 hours, with the greatest increases occurring in areas with the greatest temperature
463 increase, such as on southwest-facing slopes (Fig. 5a). The total increase in growing degree-
464 days varied by more than a factor of 5, ranging from 51 °C days on north-east facing slopes at
465 higher altitudes, to 267 °C days on steep southwest-facing slopes (Fig. 5b). Changes in the
466 length of the frost-free season also varied substantially, with marginal decreases of up to 11
467 days along sheltered river valleys subject to cold-air drainage, but substantial increases of up
468 to 54 days along eastern coastal regions of our study area (Fig. 5c). Here, the strong east-west

469 gradient is driven primarily by the overall likelihood of frost, which is markedly lower in
470 western coastal areas.

471

472 Closer inspection of the individual components of our model that most contribute to the
473 spatial variation in warming suggests that the effects of solar radiation are most important
474 (Fig. S9 in Appendix S3). This appears to have manifested itself in two ways. First,
475 reductions in daytime cloud cover (Fig. 3c) have resulted in a general increase in direct
476 radiation received at each cell, which in turn means that grid cells receiving high radiation
477 have warmed by more than those receiving less radiation (Fig S9a). Second, reductions in the
478 westerly wind vector (Fig. 3g), and the concomitant increase in easterly winds, appears to
479 have had the dual effects of decreasing the effects of radiation on these slopes (Fig S9c) and
480 increasing coastal effects towards the east of our study area, particularly during periods of
481 slow rises in sea temperature (Fig 3b).

482

483 **Discussion**

484 *Model performance*

485 Our model provides reliable estimates of local temperatures, and demonstrates the potential
486 advantage of modelling the physical processes that drive climatic variation, albeit that
487 assumptions must be made about the functional relationships between temperature and the
488 features that influence this. It also provides finer-grained and more accurate estimates than
489 previous physical-based models (Gunton *et al.*, 2015, Kearney *et al.*, 2014). Nonetheless, it is
490 not surprising that our model provides more accurate estimates than attempts to model
491 continent-wide local temperatures, as the geographical characteristics and weather patterns
492 that influence local temperature anomalies are likely to vary by region. Attempts to model

493 local ground temperatures based on local radiation budgets and weather station data situated
494 within a few hundred metres of a study area, such that meso-climatic variation is implicitly
495 accounted for, have resulted in models capable of estimating in excess of 90% of local
496 variation in temperature (Bennie *et al.*, 2008), emphasising that it is the influence of regional
497 air flows on temperature rather than the effects of local radiation that are more difficult to
498 model reliably. At fine scales, in the order of millimetres to metres, it is local radiation that
499 dominates the earth's energy budget, whereas at scales of metres to kilometres, the horizontal
500 and vertical transfer of energy by moving air-masses becomes increasingly important
501 (Geiger, 1965).

502

503 Nonetheless, over the extent of our study area, local variation in net solar radiation appears to
504 be the dominant driver of variation in temperature, and it is thus worth highlighting that there
505 are at least three limitations associated with our ability to capture the effects of this variation.
506 First, because we have attempted to model long term changes in temperature, our estimates of
507 incoming short-wave radiation are based on crude estimates of cloud cover at a single point
508 location. Incoming radiation, as well as being affected by spatial variation in cloud cover, is
509 also affected by cloud thickness and atmospheric conditions, notably by the concentration of
510 aerosols and atmospheric gases (Kasten, 1996, Twomey, 1991). Spatial and temporal
511 variation in these is unaccounted for by our model, and is likely to account for much of the
512 unexplained variance in local temperatures. Second, our model makes no attempt to account
513 for the effects of vegetation. Vegetation is known to have strong influence on local
514 temperatures, and although these differences are greatest closest to the ground (Suggitt *et al.*,
515 2011), canopy cover and leaf area density affect solar radiation budgets (Kuuluvainen &
516 Pukkala, 1989). Our temperature loggers were all located in areas with minimal canopy cover
517 and our model is intended to be of temperatures in habitat types in which temperatures a

metre above the ground are not strongly affected by vegetative shading. Lastly, for the purposes of efficiently modelling hourly temperatures, we use a simple linear relationship between net radiation and temperature, thus making the assumption that soil heat flux is relatively small and temperatures rapidly achieve equilibrium with environmental conditions (see also Bennie *et al.*, 2008). While it is likely that heat exchange may cause time-lags between radiation and temperature, perhaps a greater consideration is the scale-dependency of effects of topographic variation on the radiation budget. Estimates of slope and aspect for a 100 m grid cell essentially average the fine-scale variation in these measures. However, the aggregated effects on radiation of this variation may scale non-linearly with coarse-scale estimates of radiation, perhaps explaining why our model fails to capture perfectly the local temperature extremes. Future efforts to model local temperatures might benefit from exploring these non-linearities. Further improvements in modelling are also likely to be obtained by explicitly accounting for the effects of land-sea temperature gradients on coastal wind processes (e.g. Savijärvi, 2004), and by more sophisticated modelling of katabatic flows (e.g. Manins & Sawford, 1979). Our existing model provides poor representation of the effects of slope steepness on pooling and the cumulative time over which pooling occurs.

Overall, however, our study demonstrates the possibility of predicting temperatures at high spatial resolution and frequency using readily available data. We believe that the process of statistically calibrating variables that capture underlying physical processes ensures that a good combination of utility, analytical tractability and robustness, particularly to novel conditions, is achieved.

540

541 *Spatial variation in climatic change*

542 The results of this study provide evidence that there is at least some fine-scale variation in
543 rates of warming, with rates of warming typically higher on southwest-facing slopes and in
544 this respect, are similar to those of Ashcroft *et al.*, (2009) who also demonstrate fine scale
545 variation in rates of warming, with higher warming on equatorward-facing slopes. While our
546 results suggest that the variation in rates of warming is relatively moderate, being only ~20%
547 higher on southwest-facing slopes, it is important to note that even moderate variation in
548 temperature change manifests itself in substantial variation in the rate of change in
549 biologically-meaningful climate variables. Overall increases in growing-degree days varied
550 by more than a factor of five, and changes in exposure to high temperatures varied from a
551 decrease to a marked increase. The greatest variation was, however, observed in the length of
552 the frost free-season. Sheltered valleys subject to cold-air drainage have experienced a
553 shortening in the frost-free season, likely due to the increase in clear-sky conditions, whereas
554 coastal fringes in the east of our study area have experienced an increase of over a month.
555 Our results emphasise that in frost-rare environments even minor temperature changes can
556 lead to a large change in the likelihood of frost and spatial variation in the prevalence of frost
557 is amplified substantially.

558

559 These variations in bioclimatic variables imply that organisms occupying different parts of
560 the landscape will experience variable rates of change. We emphasise that it is not the
561 existence of cool microclimate *per se* that leads to the potential existence of microrefugia, but
562 it is the extent to which changes in weather conditions lead to thermal decoupling of local
563 trends in temperature change from those occurring regionally.

564

565 Across our study area and over the duration for which our model provides estimates of
566 temperature, there appear to be two dominant trends in weather conditions that account for

567 the variation in temperature increase. First, daytime cloud cover has generally declined, with
568 a particularly substantial decline over the period between the early 1990s and 2010. As a
569 consequence net solar radiation has increased, with the overriding effect that the temperature
570 rise is amplified in areas receiving more radiation. In consequence, cooler microclimates are
571 also those that have experienced the least change. Second, there has been a decline in
572 westerly airflow, and west-facing slopes have thus become less exposed to wind, which has
573 the effect of reducing the degree of thermal coupling of the surface to the atmosphere (Bennie
574 *et al.*, 2008, Geiger, 1965). The overriding influence of this on temperature change is that the
575 effects of increasing radiation are amplified on west-facing slopes. A secondary effect is,
576 however, evident during periods in which sea-surface temperatures increased more slowly
577 than land temperatures, such as between 2010 and 2014. In these circumstances, the
578 attenuating effect of sea temperatures on coastal land temperatures appears to be counteracted
579 on westerly seabards, by the reduction in coastal influences caused by reductions in westerly
580 winds. On eastern seabards, however, the attenuating effects of the sea are magnified,
581 resulting in a strong east-west gradient in temperature increase.

582

583 In common with other studies (e.g. Ashcroft *et al.*, 2009, Dobrowski, 2011, Hylander *et al.*,
584 2015), our results emphasise the importance of changes in weather patterns in driving local
585 variation in temperature change, but also provide additional mechanistic insight into the
586 factors responsible. Our findings are also supported by research on the long-term trends in the
587 prevalence of different weather types in the North Atlantic, particularly those associated with
588 weather patterns in Spring and Summer (Philipp *et al.*, 2007). Conditions associated with
589 blocking highs over Great Britain, characterised by high pressure and clear skies have
590 increased sharply, particularly in Spring, likely accounting for the reduction in cloud cover
591 and potentially also the reduction in westerly airflow. It is important to emphasise, however,

592 that there is little evidence for uninterrupted long-term trends in the prevalence of synoptic
593 weather conditions, and the majority undergo multi-decadal variation (Philipp *et al.*, 2007). In
594 consequence, the localities least vulnerable to warming are prone to change, and microrefugia
595 should be best viewed as temporary holdouts (see Hannah *et al.*, 2014 for further details of
596 this concept). In the context of future climatic change, however, one likely effect is the
597 slower rise in sea-surface temperatures relative to those on land (IPCC 2014). While in our
598 study, the impacts of this are masked by trends in weather patterns, and the strong maritime
599 influence across our entire study area, in most parts of the world coastal regions have
600 undergone less temperature change. The effects of coastal buffering are evident in coarser-
601 scale climatic variation across the UK (Jenkins, 2007), but are also likely to occur at finer
602 scales. Overall, the influence of changes in weather conditions is unlikely to be unique to our
603 study area and our findings thus provide insight into how trends in weather conditions may
604 influence local variation in temperature change.

605 *Ecological implications*

606 Understanding spatial variation in rates of warming could act as a foundation for addressing
607 the discrepancy between the scales at which organisms experience climatic changes and those
608 at which climatic effects are typically measured and modelled (Potter *et al.*, 2013) and may
609 serve to identify locations where species are less vulnerable to climate change or where
610 management could be targeted to offset the effects of climate change (Greenwood *et al.*,
611 2016). For example, the wall brown butterfly (*Lasiommata megera*) has undergone
612 widespread population extinctions due to warming temperatures in Northern Europe, but rates
613 of decline are lower in areas experiencing less warming (Van Dyck *et al.*, 2015).

614

615 The results of our study also help to elucidate the physical processes that define and create
616 microrefugia. Our study suggests that the locations of microrefugia are likely to be influenced

617 strongly by long-term trends in weather patterns, but in common with previous work
618 (Ashcroft *et al.*, 2009), the places experiencing the least warming under recent conditions are
619 also those with coolest microclimates. The premise that ecological communities in such
620 locations may be buffered against the effects of climatic change is also supported by the
621 evidence that, within our study area, 30-year temperature-driven changes in plant
622 communities are lower on north-east facing slopes (Maclean *et al.*, 2015).

623

624 Our study provides strong evidence that trends in synoptic weather patterns result in spatially
625 variable rates of warming across a landscapes, leading to substantial spatial heterogeneity in
626 biologically relevant climate variables. Most significant is the variation in the length of the
627 frost-free season, which has slightly decreased at higher altitude inland, but has increased by
628 over a month in south-east facing coastal regions. It is important to emphasise, however, that
629 the long-term consistency in the locations least vulnerable to climatic changes are likely to be
630 linked to long-term weather trends and may thus be ephemeral. Nonetheless, much of the
631 ecology of long-term climatic change is likely to be occurring at finer scales than is currently
632 appreciated. Methods that allow these changes to be quantified are much needed if these
633 remaining uncertainties are to be resolved.

634

635 **Acknowledgements**

636 We thank Michael Ashcroft, Richard Gunton and an anonymous referee for helpful
637 comments on the manuscript and Ray Lawman and Rachel Holder for permission to deploy
638 data loggers on land owned by or managed by the National Trust and Natural England. This
639 research was partly funded by the European Social Fund (09099NCO5), NERC
640 ((NE/L00268X/1) and by Natural England.

641

642 **References**

- 643 Allen RG, Pereira LS, Raes D, Smith M (1998) Crop evapotranspiration - Guidelines for
644 computing crop water requirements - FAO Irrigation and Drainage Paper 56. *FAO,*
645 *Rome.*
- 646 Ashcroft MB, Chisholm LA, French KO (2009) Climate change at the landscape scale:
647 predicting fine-grained spatial heterogeneity in warming and potential refugia for
648 vegetation. *Global Change Biology*, **15**, 656-667.
- 649 Barr S, Orgill MM (1989) Influence of external meteorology on nocturnal valley drainage
650 winds. *Journal of Applied Meteorology*, **28**, 497-517.
- 651 Bennie J, Huntley B, Wiltshire A, Hill MO, Baxter R (2008) Slope, aspect and climate:
652 spatially explicit and implicit models of topographic microclimate in chalk grassland.
653 *Ecological Modelling*, **216**, 47-59.
- 654 Bennie J, Wilson RJ, Maclean IMD, Suggitt AJ (2014) Seeing the woods for the trees - when
655 is microclimate important in species distribution models? *Global Change Biology*, **20**,
656 2699-2700.
- 657 Clark JS, Fastie C, Hurtt G *et al.* (1998) Reid's Paradox of Rapid Plant Migration Dispersal
658 theory and interpretation of paleoecological records. *BioScience*, **48**, 13-24.
- 659 Dobrowski SZ (2011) A climatic basis for microrefugia: the influence of terrain on climate.
660 *Global Change Biology*, **17**, 1022-1035.
- 661 Evans MR (2012) Modelling ecological systems in a changing world. *Philosophical
662 Transactions of the Royal Society B: Biological Sciences*, **367**, 181-190.
- 663 Forsythe GE, Malcolm MA, Moler CB (1977) *Computer Methods for Mathematical
664 Computations*. Wiley, New York.

- 665 Franklin J, Davis FW, Ikegami M, Syphard AD, Flint LE, Flint AL, Hannah L (2013)
666 Modeling plant species distributions under future climates: how fine scale do climate
667 projections need to be? *Global Change Biology*, **19**, 473-483.
- 668 Fritsch A, Ickstadt K (2009) Improved criteria for clustering based on the posterior similarity
669 matrix. *Bayesian Analysis*, **4**, 367-391.
- 670 Geiger R (1965) *The Climate Near the Ground*. Harvard University Press, Cambridge MA.
- 671 Gillingham P, Huntley B, Kunin W, Thomas C (2012) The effect of spatial resolution on
672 projected responses to climate warming. *Diversity and Distributions*, **18**, 990-1000.
- 673 Greenwood O, Mossman HL, Suggitt AJ, Curtis RJ, Maclean IMD (2016) Using in situ
674 management to conserve biodiversity under climate change. *Journal of Applied
675 Ecology*, in press. DOI: 10.1111/1365-2664.12602
- 676 Gunton RM, Polce C, Kunin WE (2015) Predicting ground temperatures across European
677 landscapes. *Methods in Ecology and Evolution*, **6**, 232-242.
- 678 Gustavsson T, Karlsson M, Bogren J, Lindqvist S (1998) Development of temperature
679 patterns during clear nights. *Journal of Applied Meteorology*, **37**, 559-571.
- 680 Hannah L, Flint L, Syphard AD, Moritz MA, Buckley LB, McCullough IM (2014) Fine-grain
681 modeling of species' response to climate change: holdouts, stepping-stones, and
682 microrefugia. *Trends in Ecology & Evolution*, **29**, 390-397.
- 683 Haugen R, Brown J (1980) Coastal-inland distributions of summer air temperature and
684 precipitation in northern Alaska. *Arctic and Alpine Research*, **12**, 403-412.
- 685 Hijmans RJ, Cameron SE, Parra JL, Jones PG, Jarvis A (2005) Very high resolution
686 interpolated climate surfaces for global land areas. *International Journal of
687 Climatology*, **25**, 1965-1978.

- 688 Hofierka J, Šúri M (2002) The solar radiation model for Open source GIS: implementation
689 and applications. In: *Proceedings of the Open source GIS-GRASS users conference*,
690 Trento, Italy, 11–13 September.
- 691 Hylander K, Ehrlén J, Luoto M, Meineri E (2015) Microrefugia: Not for everyone. *Ambio*,
692 **44**, 60-68.
- 693 IPCC (2014) *Climate Change 2013: The Physical Science Basis* (eds Stocker T, Qin D,
694 Plattner G-K *et al.*), Cambridge University Press, Cambridge.
- 695 Jenkins GJ (2007) *The Climate of the United Kingdom and Recent Trends*, Met Office
696 Hadley Centre, Exeter.
- 697 Kasten F (1996) The Linke turbidity factor based on improved values of the integral Rayleigh
698 optical thickness. *Solar Energy*, **56**, 239-244.
- 699 Kasten F, Young AT (1989) Revised optical air mass tables and approximation formula.
700 *Applied Optics*, **28**, 4735-4738.
- 701 Kearney MR, Shamakhy A, Tingley R, Karoly DJ, Hoffmann AA, Briggs PR, Porter WP
702 (2014) Microclimate modelling at macro scales: a test of a general microclimate
703 model integrated with gridded continental-scale soil and weather data. *Methods in*
704 *Ecology and Evolution*, **5**, 273-286.
- 705 Kuuluvainen T, Pukkala T (1989) Simulation of within-tree and between-tree shading of
706 direct radiation in a forest canopy: effect of crown shape and sun elevation.
707 *Ecological Modelling*, **49**, 89-100.
- 708 Lassueur T, Joost S, Randin CF (2006) Very high resolution digital elevation models: Do
709 they improve models of plant species distribution? *Ecological Modelling*, **198**, 139-
710 153.
- 711 Maclean IMD, Bennie JJ, Scott AJ, Wilson RJ (2012) A high-resolution model of soil and
712 surface water conditions. *Ecological Modelling*, **237**, 109-119.

- 713 Maclean IMD, Hopkins JJ, Bennie J, Lawson CR, Wilson RJ (2015) Microclimates buffer the
714 responses of plant community to climate change. *Global Ecology and Biogeography*,
715 **24**, 1340-1350.
- 716 Manins P, Sawford B (1979) A model of katabatic winds. *Journal of the Atmospheric*
717 *Sciences*, **36**, 619-630.
- 718 McGregor G, Bamzelis D (1995) Synoptic typing and its application to the investigation of
719 weather air pollution relationships, Birmingham, United Kingdom. *Theoretical and*
720 *Applied Climatology*, **51**, 223-236.
- 721 Pepin N, Daly C, Lundquist J (2011) The influence of surface versus free-air decoupling on
722 temperature trend patterns in the western United States. *Journal of Geophysical*
723 *Research: Atmospheres*, **116**, D10109.
- 724 Philipp A, Della-Marta P-M, Jacobbeit J, Fereday DR, Jones PD, Moberg A, Wanner H (2007)
725 Long-term variability of daily North Atlantic-European pressure patterns since 1850
726 classified by simulated annealing clustering. *Journal of Climate*, **20**, 4065-4095.
- 727 Phillips BL, Brown GP, Travis JM, Shine R (2008) Reid's paradox revisited: the evolution of
728 dispersal kernels during range expansion. *The American Naturalist*, **172**, S34-S48.
- 729 Pike G, Pepin N, Schaefer M (2013) High latitude local scale temperature complexity: the
730 example of Kevo Valley, Finnish Lapland. *International Journal of Climatology*, **33**,
731 2050-2067.
- 732 Posselt R, Müller R, Stöckli R, Trentmann J (2011) *CM SAF surface radiation MVIRI Data*
733 *Set 1.0—Monthly means/daily means/hourly means*. Satellite Application Facility on
734 Climate Monitoring.
- 735 Potter KA, Arthur Woods H, Pincebourde S (2013) Microclimatic challenges in global
736 change biology. *Global Change Biology*, **19**, 2932-2939.

- 737 R Development Core Team (2013) *R: A Language and Environment for Statistical*
738 *Computing*. Vienna, Austria.
- 739 Randin CF, Engler R, Normand S *et al.* (2009) Climate change and plant distribution: local
740 models predict high-elevation persistence. *Global Change Biology*, **15**, 1557-1569.
- 741 Rayner N, Parker DE, Horton E *et al.* (2003) Global analyses of sea surface temperature, sea
742 ice, and night marine air temperature since the late nineteenth century. *Journal of*
743 *Geophysical Research: Atmospheres*, **108**, D14.
- 744 Rice K (2004) Sprint research runs into a credibility gap. *Nature*, **432**, 147-147.
- 745 Rull V (2009) Microrefugia. *Journal of Biogeography*, **36**, 481-484.
- 746 Ryan BC (1977) A mathematical model for diagnosis and prediction of surface winds in
747 mountainous terrain. *Journal of Applied Meteorology*, **16**, 571-584.
- 748 Savijärvi H (2004) Model predictions of coastal winds in a small scale. *Tellus*, **56**, 287-295.
- 749 Scherrer D, Körner C (2011) Topographically controlled thermal-habitat differentiation
750 buffers alpine plant diversity against climate warming. *Journal of Biogeography*, **38**,
751 406-416.
- 752 Sebastiá M-T (2004) Role of topography and soils in grassland structuring at the landscape
753 and community scales. *Basic and Applied Ecology*, **5**, 331-346.
- 754 Stacey FD, Davis PM (1977) *Physics of the Earth*. Wiley New York.
- 755 Stewart JR, Lister AM (2001) Cryptic northern refugia and the origins of the modern biota.
756 *Trends in Ecology & Evolution*, **16**, 608-613.
- 757 Suggitt A, Wilson R, August T *et al.* (2014) Climate change refugia for the flora and fauna of
758 England. Natural England, Peterborough.
- 759 Suggitt AJ, Gillingham PK, Hill JK, Huntley B, Kunin WE, Roy DB, Thomas CD (2011)
760 Habitat microclimates drive fine-scale variation in extreme temperatures. *Oikos*, **120**,
761 1-8.

- 762 Twomey S (1991) Aerosols, clouds and radiation. *Atmospheric Environment. Part A. General*
- 763 *Topics*, **25**, 2435-2442.
- 764 Tzedakis P, Emerson B, Hewitt G (2013) Cryptic or mystic? Glacial tree refugia in northern
- 765 Europe. *Trends in Ecology & Evolution*, **28**, 696-704.
- 766 Van Dyck H, Bonte D, Puls R, Gotthard K, Maes D (2015) The lost generation hypothesis:
- 767 could climate change drive ectotherms into a developmental trap? *Oikos*, **124**, 54-61.
- 768 Willis KJ, Bhagwat SA (2009) Biodiversity and climate change. *Science*, **326**, 806.

769 **Supporting information**

770 Additional Supporting Information may be found in the online version of this article:

771

772 **Appendix S1.** R code for functions referred to in the text.

773 **Appendix S2.** Accompanying documentation for R functions referred to in the text.

774 **Appendix S3.** Detailed assessment of model performance.

775 **Appendix S4.** Spatial variation in trends in bioclimate variables in each 100m grid cell.