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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

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Abstract

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

Introduction

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

The existence of fine-grain heterogeneity has prompted suggestions that species may be able to survive future climatic change by exploiting pockets of suitable microclimate, often termed 'microrefugia' (Hannah *et al.*, 2014, Rull, 2009). The term 'microrefugia' is borrowed from paleoecology and is usually used to describe locations with unusual microclimate in which isolated populations survive unsuitable regional climate (Rull, 2009). After the Last Glacial Maximum, many species recolonized parts of their historic range at rates much faster than predicted from dispersal models (Clark *et al.*, 1998). While long-distance dispersal may be important in explaining this phenomenon (Phillips *et al.*, 2008), an alternative explanation is that species recolonized from localities with suitable microclimate much closer to their former range (Stewart & Lister, 2001). Nonetheless, the possible existence of microrefugia is 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 (50º 2'N, 5º 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

6

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 ° 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 49-51ºN and 4-6ºW. 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 (0º, 10º…350º) 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 5250ºC 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 0.03º 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 & Ŝúri (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 Kaston 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 & Ŝúri (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 9.8ºC 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 6ºC 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 2ºC

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

270   temperature. As calculation of condensation and evapotranspiration relies on knowledge of

271   local temperatures, but in this instance is also used to derive local temperatures, we used the

272   local temperature anomaly (i.e. the difference between modelled local temperature and that at

273   the meteorological station) in the previous time step, to derive estimates of local differences

274   in latent heat exchange from our reference meteorological station. We assume condensation

275   occurs when drops in temperature result in relative humidity exceeding 100%. First, from

276   Allen *et al.* (1998) we calculate the local relative humidity as a function of the relative

277   humidity measured at the met station, saturated vapour pressure and absolute humidity, which

278   is assumed to remain constant, thus allowing local relative humidity to exceed 100%

279   (function *rh.change* in Appendix S1). Where local relative humidity is less than 100%,

280   condensation is assumed not to occur, but where relative humidity would exceed 100% as a

281   result of temperature decreases, the surplus water is assumed to condense (function

282   *water.conden* in Appendix S1). Following Allen *et al.* (1998) potential evapotranspiration

283   was calculated as a function of net radiation, local temperatures (estimated from anomalies in

284   the previous time step), relative humidity, atmospheric pressure and wind speed using the

285   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

295 calculated the following meteorological variables from the meteorological station data,

296 aggregating data into 24-hour averages: (i) cloud cover (oktas), (ii) mean temperature (ºC),

297 (iii) diurnal temperature range (ºC), (iv) surface atmospheric pressure (hPA), (v) relative

298 humidity (%), (vi) wet bulb temperature (ºC), (vii) the dew point temperature (ºC), (viii)

299 visibility (km), (ix) net radiation (MJ m^{-2} hr^{-1}), (x) the westerly wind component (m s^{-1}) and

300 (xi) the southerly wind component (m s^{-1}). Visibility data were log-transformed to reduce

301 heteroscedasticity and all variables were z-score standardised. Meteorological variables were

302 also de-seasoned by applying a 15 day running mean filter. Second, as the resulting variables

303 were highly correlated with one another, we performed principal components analysis (PCA).

304 To determine how many components to retain, we produced a scree plot, retaining four

305 components which together explained 85% of the variance in the original data. Finally we

306 performed Bayesian model-based clustering on these data using the R package mclust

307 (Fritsch & Ickstadt, 2009), to group our data into distinct synoptic weather types. Using this

308 approach, prior cluster partitions are identified using hierarchical agglomeration, and then

309 Bayesian expectation-maximization is performed to automatically identify the final cluster

310 number and membership thereof. Seven was considered the most likely number of distinct

311 synoptic weather types using this method (see results). The synoptic weather type

312 characterised by clear sky, high pressure, a high diurnal temperature range, good visibility

313 and low relative humidity was considered to be the conditions under which temperature

314 inversions occur (see e.g. Barr & Orgill, 1989). Temperature inversions were set to occur at

315 night only as daytime cold air drainage into valleys is highly unusual in maritime climates

316 (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: $u_i L + u_1 L + L T_s$

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

14

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 20ºC, growing

370 degree-days were calculated as the difference between mean daily temperatures and a base

371 temperature of 10ºC, with temperatures capped at 30ºC 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 to 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**

16

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 ºC and RMS error of 1.63ºC. 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 ºC 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 ºC (95% CI = 0.21 to 1.57, n = 649; Fig. 3b). Among other weather

17

419 variables, there were two notable trends. First, linear regression on hourly estimates reveals

420 that although cloud cover has changed little (<0.2%) over the duration of the study (95% CI =

421 -0.49% to 0.15%, n = 333096), daytime cloud cover decreased by 4.0% (95% CI = -5.1% to -

422 2.9%, n = 166602; Fig. 3c), whereas night-time cloud cover increased by 1.2% (95% CI =

423 0.7% to 1.7%, n = 166602; Fig. 3d). Changes in cloud cover appear to have manifested

424 themselves in moderate increases in received solar radiation: direct radiation was estimated to

425 have increased by 11.9 Wm^{-2} over the period of the study (95% CI = 5.2 to 18.7, n =333096;

426 Fig. 3e). However, diffuse radiation has changed little (95% CI = -2.8 to 7.0 Wm^{-2}, n

427 =333096; Fig. 3f).

428

429 Second, there appears to have been a shift in wind vectors. Linear regression of hourly values

430 reveals a decrease in zonal (west to east) wind velocity of 0.66 ms^{-1} over the duration of the

431 study (n =333096, 95% CI = -0.71 to -0.60; Fig. 3g) and a decrease in meridional wind

432 velocity (the northerly wind component) of 0.44 ms^{-1} (n =333096, 95% CI = -0.49 to -0.39;

433 Fig. 3h). Somewhat paradoxically, however, the synoptic weather type associated with

434 easterly winds, weather type 1, also indicative of weakly anticyclonic conditions, high

435 pressure and high relative humidity, decreased by 2.2% from 10.1% to 8.0% (n=38, 95% CI

436 = -4.3 to -1.3%) and was the only type for which a trend was evident (Fig S6). The most

437 likely explanation of this is that while the mean zonal component of the wind vector in any

438 given year remained relatively constant over time during periods in which synoptic weather

439 type 1 prevailed (95% CI = -0.93 to 1.01 ms^{-1}, n=38), the zonal component in any given year

440 during periods in which synoptic weather types other than type 1 prevailed, decreased

441 substantially (-1.75 ms^{-1} over the duration of the study; 95% CI = -1.41 to -2.09 ms^{-1}, n=38).

442

443

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 0.87ºC to 1.16ºC, 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 Culdrose rose by 2.30 ºC in comparison to sea-surface

451 temperatures rising by 1.34 ºC (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 (>20ºC) 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 ºC days on north-east facing slopes at

465 higher altitudes, to 267 ºC 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 clover, 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

518   metre above the ground are not strongly affected by vegetative shading. Lastly, for the

519   purposes of efficiently modelling hourly temperatures, we use a simple linear relationship

520   between net radiation and temperature, thus making the assumption that soil heat flux is

521   relatively small and temperatures rapidly achieve equilibrium with environmental conditions

522   (see also Bennie *et al.*, 2008). While it is likely that heat exchange may cause time-lags

523   between radiation and temperature, perhaps a greater consideration is the scale-dependency

524   of effects of topographic variation on the radiation budget. Estimates of slope and aspect for a

525   100 m grid cell essentially average the fine-scale variation in these measures. However, the

526   aggregated effects on radiation of this variation may scale non-linearly with coarse-scale

527   estimates of radiation, perhaps explaining why our model fails to capture perfectly the local

528   temperature extremes. Future efforts to model local temperatures might benefit from

529   exploring these non-linearities. Further improvements in modelling are also likely to be

530   obtained by explicitly accounting for the effects of land-sea temperature gradients on coastal

531   wind processes (e.g. Savijärvi, 2004), and by more sophisticated modelling of katabatic flows

532   (e.g. Manins & Sawford, 1979). Our existing model provides poor representation of the

533   effects of slope steepness on pooling and the cumulative time over which pooling occurs.

534

535   Overall, however, our study demonstrates the possibility of predicting temperatures at high

536   spatial resolution and frequency using readily available data. We believe that the process of

537   statistically calibrating variables that capture underlying physical processes ensures that a

538   good combination of utility, analytical tractability and robustness, particularly to novel

539   conditions, is achieved.

540

541   *Spatial variation in climatic change*

22

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

23

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 seaboards, by the reduction in coastal influences caused by reductions in westerly

580   winds. On eastern seaboards, 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

641

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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 documention 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.