

1 **The effect of spatial resolution on projected responses to climate warming.**

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25 Running Title: Future habitat suitability varies with resolution.

26

27 **(A) ABSTRACT**

28

29 **(B) Aim**

30 To determine how changing the resolution of modelled climate surfaces can affect estimates
31 of the amount of thermally suitable habitat available to species under different levels of
32 warming.

33

34 **(B) Location**

35 Lake Vyrnwy RSPB Reserve, which covers around 9,700 hectares of a topographically
36 diverse landscape in Wales.

37

38 **(B) Methods**

39 A recently published microclimate model was used to predict maximum, minimum and mean
40 temperatures at 5 x 5 m resolution for the study site, under current and possible future
41 conditions. These temperature surfaces were then averaged to produce coarser resolution
42 surfaces, up to a maximum of 1 x 1 km resolution. Ground beetles were collected using pitfall
43 traps between May and August 2008. GLMs were fitted to the temperature surfaces to predict
44 the amount of landscape suitable for a northerly-distributed ground beetle, *Carabus*
45 *glabratus*, and the most southerly distributed ground beetle found at the site, *Poecilus*
46 *versicolor*, under current and possible future conditions.

47

48 **(B) Results**

49 A wider range of temperatures are expected within our site when temperature is modelled at
50 finer resolutions. Fitting GLMs at different resolutions resulted in the inclusion of different

51 temperature variables in the best models. Coarser resolution models tended to have higher
52 prediction error, and different resolution models predicted that different amounts of the
53 landscape would remain or become suitable in future. There was less agreement between
54 models for *C. glabratus* than for *P. versicolor*.

55

56 **(B) Main Conclusions**

57 In our example system, different resolution analyses result in different predictions about the
58 ability of populations to survive climatic warming. Higher resolution analyses are not only
59 likely to provide more accurate estimates of expected patterns of change, but also to highlight
60 potential microclimatic refugia for the conservation of species that otherwise might appear to
61 be threatened with regional or global extinction.

62

63 **(B) Keywords**

64 *Carabus glabratus*, Climate change, Coleoptera, conservation, distribution models,
65 extinction, *Poecilus versicolor*.

66

67 **(A) INTRODUCTION**

68

69 Many studies use climatic variables such as temperature to define the range of conditions that
70 species can occupy. At large spatial extents, such climatic variables are commonly found to
71 be associated with the presence and absence of species (Peterson, 2001). Environmental
72 “niche” or “bioclimate” models, which are based on the associations of species’ distributions
73 with climatic variables, are often then used to predict changes in the area available to species
74 following future climatic change (e.g. Huntley *et al.*, 1995; Leathwick *et al.*, 1996; Peterson
75 *et al.*, 2001; Thomas *et al.*, 2004; Elith & Leathwick, 2009; Kearney *et al.*, 2010; Bellard et al

76 2012) and changes in species' richness within an area following climatic warming (Hannah *et*
77 *al.*, 2005; Menéndez *et al.*, 2006; Huntley *et al.*, 2007). In the past, these climate envelope
78 studies have normally considered the associations between climate and species' distributions
79 at relatively coarse resolutions (usually 1 km² or coarser; commonly around 100 km²
80 resolution in Britain, or 2500 km² in Europe). This corresponds to the availability of species'
81 distribution data (e.g. National Biodiversity Network, NBN, <http://data.nbn.org.uk>) and/or of
82 climate surfaces; and gives the capacity to run models quickly for large geographic areas. It
83 also corresponds to resolution at which climate is perceived to be an important factor when
84 determining distributions (McGill, 2010). However, a recent study suggested that climate can
85 be important at finer resolutions (Gillingham *et al.*, 2012). In addition, some distribution
86 records are submitted with greater spatial precision and climate surfaces are increasingly
87 downscaled to finer resolutions (Guan *et al.*, 2009) as computational power continues to
88 increase. This makes the prospect of producing fine-resolution bioclimate models
89 increasingly realistic (e.g. Montoya *et al.*, 2009; Seo *et al.*, 2009). Here we consider the
90 implications of modelling distribution change at different spatial resolutions.

91

92 A number of previous studies suggest that the spatial resolution of analysis could affect
93 estimates of species declines and extinction. Thomas & Abery (1995) found that the observed
94 decline rates of 12 British butterfly species were 35 % higher when estimated using a 4 km²
95 grid than when based on a 100 km² grid. For *Plebejus argus*, the loss of 90 % of the local
96 populations resulted in a loss of only 56 % of 4 km² grid squares. Similarly, Thomas *et al.*,
97 (2006) found that much higher rates of retraction at low latitude/elevation range boundaries
98 were detected when they were measured using a 1 km² grid than when using a 100 km² grid.
99 This may be a particular issue in mountainous regions, where coarse-resolution grid cells may
100 contain a wide range of environments and population densities (Shoo *et al.*, 2006). Within

101 such a grid square, there is likely to be a wide range of microclimatic conditions (Ashcroft *et*
102 *al.*, 2009), potentially resulting in the presence of locally-suitable conditions for species at
103 their thermal margins, the existence of which might not be apparent at a coarser resolution.
104 Many species are associated with locally suitable microclimates at their range margins, where
105 the coarser-scale mean climate is less suitable than at the centres of their ranges (Thomas *et*
106 *al.*, 1999; Bryant *et al.*, 2002; Lennon *et al.*, 2002; Stefanescu *et al.*, 2004). Thus, models that
107 utilise fine resolution data should be more accurate than those using coarse resolution climate
108 data (Ferrier *et al.*, 2002) in areas of high relief and for predicting the likely persistence of
109 species in small areas such as individual nature reserves.

110

111 These resolution issues mean that estimates of rates of decline under climatic change may be
112 either too high or too low when using coarse resolution data and model projections. There is a
113 possibility that coarse resolution models will overestimate the area available to species
114 (Trivedi *et al.*, 2008) if, for example, a species only lives in the coldest 1 % of a coarse-
115 grained grid cell, which contains a heterogeneous mix of different microclimatic conditions,
116 but statistically appears to be able to inhabit the mean temperature of the grid square. Under
117 modest climate warming, the coldest 1 % may become unsuitable for the species, even if the
118 average temperature of the grid square still appears to remain suitable. Under this
119 circumstance, a coarse resolution model may be slow to predict the disappearance of thermal
120 refugia, and may therefore underestimate the rate of decline. Alternatively, however, fine
121 resolution models may predict the persistence of these thermal refugia for longer into the
122 future with climatic warming than do low resolution models (Randin *et al.*, 2009). So far,
123 there are very few studies that have attempted to discover whether over- or under-estimation
124 of declines is likely to be projected using coarse resolution models. Those that have been
125 attempted have been restricted to plants, which, being sessile, might be expected to have a

126 different propensity to survive in spatially restricted thermal refugia than more mobile
127 organisms.

128

129 Previous studies that explored the implications of using models at different spatial resolutions
130 interpolated fine-resolution climate surfaces using lapse rates (i.e., adjusting local
131 temperatures to take account of the local elevation; Trivedi *et al.*, 2008; Randin *et al.*, 2009).

132 However, variation in aspect and slope can have even larger effects than elevation on local
133 temperature (Suggitt *et al.*, 2011). Given this uncertainty, and contrasting conclusions in the
134 literature, it is not clear whether fine-resolution analysis is expected to predict reduced
135 (Trivedi *et al.*, 2008) or increased (Randin *et al.*, 2009) persistence, compared to coarse-
136 resolution analyses. Here, we present the first study to compare the effects of different
137 resolution models on predicted landscape suitability for a species where the effects of slope,
138 aspect, hill-shading and elevation on local temperatures are included.

139

140 In this study, we sampled the abundance of ground beetles from within a single 10 x 10 km
141 square (Figure 1). Because ground beetles are predatory, they should not be directly limited to
142 particular vegetation types, although some preferences may be caused due to the
143 microclimate experienced under different canopies. The study site is an area with substantial
144 topographic variation, which thus gives a range of predicted temperatures depending on the
145 resolution of the data (Figure 2), and sampled 1 km grid squares sometimes contained both
146 sample locations where species were present and those where they were absent (e.g. see
147 Figure 1). Because our records have a spatial precision of 5 m and include abundance data
148 rather than presence/absence data, we were able to use them to answer several questions:
149 1) How does the spatial resolution used when modelling alter our perceptions of the
150 temperatures of topographically diverse areas?

151 2) Does the projected percentage of a landscape that will remain suitable northern or southern
152 species following climatic change vary with the resolution of the distribution model?

153

154 **(A) METHODS**

155

156 **(B) Field Sampling**

157

158 Ground beetles were collected by pitfall trapping from the start of May to the end of August
159 2008. Trapping took place on the Royal Society for the Protection of Birds (RSPB) Lake
160 Vyrnwy reserve.

161

162 Lake Vyrnwy is situated adjacent to Snowdonia National Park in Wales (52° 47' 09" N,
163 03° 30' 49" W) and covers around 9,700 hectares. It contains several different vegetation
164 types, but all trapping was undertaken in heathland dominated by *Calluna vulgaris* (heather)
165 that occurs mainly on peaty soils. This heathland is actively managed for wildlife with a
166 combination of mowing, burning and grazing being employed to maintain a mosaic of
167 heather and grassland. The lowest areas of the reserve are around 350 m a.s.l., with the
168 highest around 620 m a.s.l. The location and elevational range of the site means that it is at
169 the southern range margin of many species with northerly distributions within the UK.

170

171 Stratified random sampling was used to select 40 locations. A 5 x 5 m grid was laid across
172 the landscape, then grid cells were stratified into twelve categories on the basis of
173 combinations of slope, aspect and elevation, with a thirteenth category for areas at the lowest
174 elevations; three sampling locations were then randomly positioned within each of the first 12
175 strata, and four in the last. This ensured that the full range of microclimates present at the site

176 was sampled. Sample points were georeferenced in the field using a handheld Global
177 Positioning System (Garmin GPS 60). At each sample location, five pitfall traps were
178 deployed in a circle of 2 m diameter. Traps consisted of two standard plastic vending cups of
179 7 cm diameter nested together and sunk into the soil so that the rim of the inner cup was flush
180 with the soil surface. Each trap was filled to a 2.5 cm depth with ethylene glycol antifreeze.
181 Traps were covered with a lid made up of a terracotta coloured plastic saucer suspended 11
182 cm above the ground and trap using galvanised wire. This served the dual purpose of limiting
183 liquid loss by evaporation and limiting flooding from rainfall. A surround of chicken wire
184 (mesh diameter 20 mm) completed the lid, with the aim of excluding small mammals from
185 the trap.

186

187 Traps were emptied at monthly intervals, with the antifreeze solution being replaced when
188 necessary. Catch was pooled for all five traps across the entire sampling season for each
189 location, providing a total of 18,795 trap-hours across the entire landscape. All carabid
190 beetles were identified to species. One northerly-distributed ground beetle, *Carabus*
191 *glabratus* and the most southerly distributed ground beetle, *Poecilus versicolor*, were selected
192 as examples for distributional modelling. *C. glabratus* might be expected to decline under
193 climate change, whilst *P. versicolor* is expected to benefit from climate change. Both species
194 fulfilled modelling criteria used in previous studies (see Gillingham *et al.*, 2012).

195

196 **(B) Microclimate modelling**

197

198 A recently published microclimate model, which has been ground-truthed and found to
199 perform well when predicting vegetation surface temperatures in two different
200 topographically heterogeneous landscapes (Bennie *et al.*, 2008), and additionally verified for

201 this landscape (Gillingham, 2011) was coded into C++ (Programme available on request from
202 PKG). Wind speed, air temperature and radiation data was obtained for the Vyrnwy
203 meteorological station (52° 45' 25" N, 03° 38' 45" W) from the British Atmospheric Data
204 Centre (BADC, www.badc.rl.ac.uk). A digital elevation model (DEM) at 5 x 5 m resolution
205 (hereafter referred to as 5 m resolution) and 1 m vertical precision for the site was obtained
206 from the NERC Earth Observation Data Centre (NEODC, neodc.nerc.ac.uk). Slope and
207 aspect values for each 5 m cell were calculated using standard functions in ArcMap. The
208 microclimate model used this information to generate hourly predicted temperatures at
209 vegetation surface height at 5 m resolution from the start of September 2007 until the end of
210 August 2008.

211

212 The microclimate model adjusted the temperature values from the Vyrnwy meteorological
213 station to take account of the elevation difference between the met station and each point in
214 the landscape, as well as differences in direct and indirect radiation associated with different
215 slopes and aspects at different times of the day and year (including effects of hill-shading,
216 and assuming homogenous cloud cover across the entire site; Bennie *et al.*, 2008). From these
217 hourly surfaces of predicted temperature at vegetation height, annual mean temperature,
218 maximum temperature in July (T_{\max}) and minimum temperature in December (T_{\min}) were
219 extracted for use in the distribution model at 5 m resolution.

220

221 We used interpolated, rather than directly-measured, temperatures in the present study
222 because: (a) much of the value of distribution models arises from their ability to generalise
223 from sample points to other locations (in the present and future), and hence this requires the
224 use of climatic surfaces that can be extrapolated in space and time, (b) ground beetles can
225 move over short distances (see below), and so will experience temperatures over a larger

226 spatial scale than single point measurements (logger temperatures at fixed points under a
227 heather canopy are variable), and (c) we placed five pitfall traps within each sample location,
228 so some measure of the expected “average condition” of such an area is more relevant to our
229 sample data than the temperature at a single point. Resources were not available to place
230 multiple loggers in each sample location.

231

232 **(B) Statistical Modelling**

233

234 Abundance (number of individuals trapped across the season) of *C. glabratus* and *P.*
235 *versicolor* were the response variables to which predictor variables were fitted using a
236 Generalised Linear Model (GLM) with Negative Binomial error structure and a log link
237 function. The annual mean (T_{mean}), July maximum (T_{max}) and December minimum (T_{min})
238 temperatures as calculated by the microclimate model were included as predictor variables.
239 Trapping effort, corresponding to the proportion of the trapping effort that was lost to damage
240 at each location (e.g., loss of two of the five pitfall traps at a given location in one month),
241 was included as a log-offset in all models to allow for variations in catch caused by damage
242 to pitfall traps. An indication of model fit was calculated using the function `cv.glm` in the `boot`
243 package in R. The default leave-one out cross validation was used to calculate adjusted
244 prediction error. To give an indication of how informative our models were, delta-AIC was
245 calculated by subtracting AIC of the intersect-only model from AIC of the selected model. All
246 possible models were fitted, and as the models were to be used to illustrate predicted
247 scenarios, the best model was selected as the one with lowest prediction error. However,
248 because there is co-linearity within our explanatory variables (see Table S1 in Supporting
249 Information), we fitted models in three additional ways to increase confidence in our
250 conclusions. We additionally removed correlated variables (see Tables S2-S3 and Figures S1-

251 S2), we selected the best model using Multimodel Inference (see Tables S4-S5 and Figures
252 S3-S4) and we selected the best model by backwards stepwise regression using AIC (see
253 Tables S6-S7 and Figures S5-S6). These methods have been found to be effective when
254 dealing with correlated explanatory variables (Smith *et al.*, 2009). All statistical analyses
255 were carried out in R version 2.9.0 (R Development Core Team, 2008).

256

257 Coarser resolution temperature surfaces were generated by blocking up the data in 100 m
258 increments using the mean value of the enclosed 5 m cells, to a maximum of 1 km resolution
259 (for examples see Figure 2, note that resolution refers to the length of the side of each cell,
260 such that 100 x 100 m cells are referred to as “100 m resolution”). GLMs were refitted to
261 these lower resolution layers as before. Where more than one sampling location fell within a
262 given coarse resolution cell, both abundance and trapping effort values were pooled to create
263 one value for each variable per cell, such that coarse resolution cells containing more than
264 one trapping location had much higher values for trapping effort. The trapping effort offset
265 was retained in all models *because* it reflects the way the data were collected and
266 manipulated.

267

268 We used 5 m resolution grids as the finest resolution considered for several practical and
269 biological reasons: (a) this is the finest resolution at which elevational data are widely
270 available; (b) this resolution seems relevant to the short-distance (daily, weekly) movements
271 of adults and large larvae (*P. versicolor* has been found to move 7 m per day in heathland,
272 whilst adults of other ground beetle species have been observed to move less than one metre
273 over 48 hours; Brouwers & Newton, 2009); (c) the entire durations of eggs, pupae, and
274 probably early larval instars will be contained within such an area. However, it should be
275 noted that population persistence and abundance for our example organism may also be

276 determined by larger-scale processes (e.g., average suitability at 100 m or coarser resolution),
277 and hence we should not conclude that the finest-resolution analysis is the only one of
278 relevance.

279

280 **(B) Future Projections**

281

282 The microclimate model was used to predict hourly temperature surfaces for the site for
283 temperature increases in half degree steps to 6 °C, which is the central estimate of the
284 maximum predicted by 2085 for the UK under the maximum emissions scenario
285 (<http://ukclimateprojections.defra.gov.uk>). This resulted in slightly uneven warming across
286 the site, with cooler areas warming slightly more than hotter ones, thus reducing the range of
287 available temperatures within the site. This approach was used in order to compare the effects
288 of data resolution on future predictions and it is not within the remit of our study to comment
289 on the likelihood of future scenarios of climatic change.

290

291 The 5 m resolution future temperature surfaces were again blocked to the resolutions
292 previously used, and the respective model equations derived previously were applied to these
293 future surfaces to predict the abundance of *C. glabratus* and *P. versicolor*. A threshold of one
294 or more individuals predicted to be present within a cell given a maximum sampling effort of
295 4 months of continuous capture in five pitfall traps (which corresponds to our sampling
296 season with no damage to traps) was used to estimate the percentage of the total landscape
297 that is expected to be climatically suitable for the species with each temperature increase,
298 based on these models. This corresponds to our ability to detect the species at any particular
299 location, if it is present. One individual present in a trap would be likely to indicate larger
300 numbers present in the immediate environment, as pitfall traps do not trap 100% of

301 individuals present, rather provide an indication of activity density (Baars, 1979). We have an
302 important caveat here. Our purpose is to illustrate the role of spatial resolution on projections,
303 and not to make a specific prognosis for *C. glabratus* or *P. versicolor*. The latter would
304 require the inclusion of more sample points and species-specific data (e.g., spatial scales of
305 movement and persistence, see above; additional prey or habitat data and a quantified
306 relationship between population density and detection probability), and testing of the
307 predictive accuracy of the regression models over a number of years. It is not within the remit
308 of this study to discover the relationship between the number of trapped individuals and
309 whether a population is viable, as this information is not available for the majority of species
310 for which climate envelope modelling is undertaken.

311

312 (A) RESULTS

313

314 (B) Microclimate surfaces

315

316 The microclimate surfaces are illustrated using July maximum temperatures (T_{\max} , see Figure
317 2). The range of T_{\max} values that appeared to exist within the landscape decreased greatly as
318 one moved from a 5 m resolution analysis (11.2 °C range; 22.4 °C to 33.6 °C) to 1000 m
319 resolution (3.9 °C range; 26.1 °C to 30.0 °C). This compares to the maximum temperature of
320 23.5 °C recorded at the Lake Vyrnwy meteorological station for July 2008 (this temperature
321 is within a Stevenson screen at 1.5 m height, and hence tends to be lower than average T_{\max}
322 values estimated for the vegetation surface). In general, as the resolution of the analysis
323 became coarser, the range of temperatures declined, with the coolest observable locations
324 being warmer and the highest observable temperatures being cooler, although this effect was
325 much less marked for T_{mean} and T_{min} (Figure 3).

326

327 **(B) Current Distributions**

328

329 For the northern species, *C. glabratus*, T_{\max} was the only independent variable apart from
330 trapping effort to be retained in the best model at 5 m resolution. It showed a negative effect
331 ($\beta = -0.91$, $n = 40$, $p < 0.0001$) on the abundance of *C. glabratus*. There were fewer *C.*
332 *glabratus* in areas with warmer summer (July) T_{\max} temperatures, as expected for a species at
333 the southern limit of its distribution. Comparable results were obtained when fitting models at
334 200 m, 600 m, and 900 m resolution.

335

336 Using the 100 m resolution temperature surface yielded a different result. Annual mean
337 temperature had a negative effect ($\beta = -1.21$, $n = 40$, $p < 0.0001$) on the abundance of *C.*
338 *glabratus*. Comparable results were achieved when fitting models at 700m and 800m
339 resolutions. The overall relationship between abundance and the three temperature variables
340 was negative at most resolutions (i.e. increasing abundance in cooler locations). However, at
341 400 m, 500 m and 1 km resolution, a positive relationship was found between temperature
342 and abundance. The coefficients fitted show a large standard error compared to the effect
343 size, so at these resolutions an effect of temperature was not seen, despite the comparatively
344 low prediction error associated with the 500 m resolution model. In addition, these models all
345 predicted the entire landscape to be suitable under current conditions, which is not the case
346 (see figure 1).

347

348 For the southern species, *P. versicolor*, annual T_{mean} was the only independent variable apart
349 from trapping effort to be retained in the best model at 5 m resolution. It showed a positive
350 effect ($\beta = 4.44$, $n = 40$, $p < 0.0001$) on the abundance of *P. versicolor*. There were more *P.*

351 *versicolor* in areas with warmer mean temperatures, as expected for a species with a more
352 southerly distribution. Comparable results were obtained when fitting models at 200 m, 400
353 m, 600 m, 800 m and 900 m resolution.

354

355 Using the 100 m resolution temperature surface again yielded a different result. T_{\max} had a
356 positive effect ($\beta = 1.44$, $n = 40$, $p = 0.0012$) on the abundance of *P. versicolor*. At 300 m and
357 700 m resolutions, T_{\min} and T_{\max} were both retained, showing a positive relationship with the
358 abundance of *P. versicolor*. In all cases, the relationship between abundance and the three
359 temperature variables was positive (i.e. increasing abundance in warmer locations).

360 For both species, prediction error varied with resolution (Tables 1 and 2). The greatest
361 prediction errors were found for models fitted at 800m resolution or coarser.

362

363 **(B) Future distributions**

364

365 Each of the above models was then applied to the entire landscape, first for the current
366 climate, and then for warming of up to 6 °C. For the northern species, *C. glabratus*, the
367 percentage of landscape perceived to be thermally suitable at current temperatures (i.e. we
368 would expect to catch one individual or more in five pitfall traps over a four month period)
369 varied from over 99 % at 100 m resolution to just over 90% at 200 m and 300 m resolutions.

370 The area projected to remain thermally suitable, following climatic warming for *C. glabratus*
371 within the study landscape, decreased in a non-linear fashion for all resolutions with
372 informative models (see Figure 4). Different resolutions of data/models resulted in different
373 rates of decline in the percentage of thermally suitable habitat associated with increasing
374 temperatures (Figure 4). Following a 3 °C rise in temperature, one model predicted that < 1
375 % of the landscape would remain suitable (100 m resolution model), whilst one model

376 predicted that 67 % of the landscape would remain suitable (800 m resolution model). The
377 rate of decline was not predictable based on the resolution of the data used to fit models.
378 However, the informative models based on different resolutions did agree on one point –
379 almost the entire landscape would be thermally unsuitable following a 6 °C rise in
380 temperature.

381

382 For the southerly-distributed *P. versicolor*, the percentage of the landscape predicted to be
383 suitable increased in a non-linear manner at all resolutions (Figure 5). At current
384 temperatures, between 29% (at 100m resolution) and just under 41% (at 900m resolution) of
385 the landscape was predicted to be suitable. There was much more agreement between
386 resolutions about the rate of increase of suitability for this species, and all models except the
387 400 m resolution model agreed that the entire landscape would be suitable following a 2 °C
388 rise in temperature.

389

390 There is an important point to be made with regard to model selection, as different model
391 selection methods resulted in different variables being retained for any one resolution for
392 both species (see Tables S2-S7). For *P. versicolor* the retention of different variables had little
393 effect on the model predictions, and agreement was high between all of the different methods
394 (Figures S2, S4 and S6). However, for *C. glabratus* the results were very different at any one
395 resolution depending on the model selection method used (Figures S1, S3 and S5). The most
396 robust conclusion is that almost all resolution models, regardless of selection method,
397 predicted that almost the entire landscape would be perceived as unsuitable following a 4 °C
398 rise in temperature.

399

400 **(A) DISCUSSION**

401

402 In a landscape such as ours, topography can change markedly over a scale of tens to hundreds
403 of metres, such that a coarser resolution cell may contain both north- and south-facing slopes,
404 as well as several hundred metres of elevational range. These differences in topography and
405 thus temperature conditions result in many coarse grid cells containing some areas that are
406 much cooler and others that are much hotter than average (Figure 2). Our analyses showed
407 that projections of future distributions are highly sensitive to this variation.

408

409 The statistical models (GLM) models that we fitted to the *current* distributions of our two
410 study species were consistent, and sensible, in that the northerly distributed *C. glabratus* was
411 mostly frequently encountered in the coolest parts of the landscape and that the southerly
412 distributed *P. versicolor* was predominantly found in the warmest locations (at all
413 resolutions). The finer resolution models generated the slowest rate of decline in the northern
414 *C. glabratus* and the slowest predicted increase in the southern *P. versicolor* (although
415 analyses for this species were far less sensitive to resolution). By modelling at resolutions far
416 coarser than the environments that individuals actually experience, we apparently
417 underestimated the capacity of northern *C. glabratus* to survive in small-scale refugia; a
418 finding typical of other studies that have used fine-resolution models (Gottfried *et al.*, 1999;
419 Williams *et al.*, 2003; Seo *et al.*, 2009), although these studies did not expressly compare
420 model resolutions. For the southern *P. versicolor*, the coarsest 1 km resolution analysis may
421 equally fail to identify warm microsites, and thereby under-estimate the potential for
422 colonisation. However, it was not as simple as this because different temperature variables
423 (annual mean, winter minimum, summer maximum) entered the models at different
424 resolutions, and under different model selection methods. This resulted in *C. glabratus*
425 appearing least sensitive to warming in some of the intermediate-resolution analyses. The

426 most conservative conclusion we can make is that that projected sensitivities to climate
427 warming are strongly dependent on the spatial resolution of analysis and the model selection
428 method. Nonetheless, we were able to find some agreement in that almost all models
429 predicted that the entire landscape would be perceived as unsuitable for *C. glabratus*
430 following a 4 °C rise in temperature.

431

432 There are two comparable studies, which reached opposite conclusions on the effect of
433 resolution on the apparent suitability of a landscape following climatic change. Randin *et al.*,
434 (2009) projected higher levels of persistence for high-resolution models of plant distributions
435 in the Swiss Alps, whilst Trivedi *et al.*, (2008) found lower projected persistence in high
436 resolution models of Scottish plants than in coarse resolution models. Both studies used
437 elevation as the sole means for interpolating temperature to finer resolutions (i.e. colder at
438 higher elevations), without considering the effects of slope and aspect. North and south
439 facing slopes can differ by as much as 7 °C (Suggitt *et al.*, 2011), so the coldest place within a
440 landscape may be on a polewards-facing slope rather than at its highest point. However,
441 topographic effects depend on the climatic variable considered (Suggitt *et al.*, 2011). Low
442 elevation areas may experience lower minimum temperatures than mid-elevations due to cold
443 air pooling (Geiger, 1973), and the highest maximum temperatures are commonly found on
444 steep south facing hillsides (in the northern hemisphere) rather than at the lowest elevations
445 (Bennie *et al.*, 2010; Suggitt *et al.*, 2011); whilst the lowest maxima (i.e. areas that are
446 suitable refugia for species preferring cooler conditions) occur at moderate rather than high
447 elevations in some landscapes (Ashcroft *et al.*, 2008), where some shelter is available from
448 hot, dry winds. Hence we suggest that elevation-only models are insufficient for high
449 resolution modelling of climatic effects on species' distributions. We suspect that the opposite
450 results of Randin *et al.*, (2009) and Trivedi *et al.*, (2008) may arise partly because of the

451 higher elevational, and hence temperature (based on lapse rate), range of Switzerland than
452 Scotland. The microclimate model we used makes a step forwards by including the effects of
453 radiation and wind speed, but there is scope for improvement by including effects such as
454 cold air pooling. In any case, modelling at a range of different resolutions, rather than just
455 coarse and fine resolution, highlighted the unpredictability of projections, with different
456 resolution models predicting different rates of decline of a northern species. Therefore, the
457 selection of different resolutions by the above-mentioned authors may be one potential source
458 of their opposite results.

459

460 The observed discrepancy between the perceptions of different resolution models, along with
461 the fact that finer resolution models have been found to perform better than coarser ones in
462 predicting species' distributions (Engler *et al.*, 2004), leads us to conclude that more
463 modelling should be done at a range of resolutions across different taxa and regions, at least
464 until we understand the circumstances leading to the prediction of higher or lower estimations
465 of extinction when fine resolution data are used. Further research on the capacities of species
466 from different taxonomic groups to persist in local microclimates is also needed. Small areas
467 of suitable microclimates do not necessarily imply that sufficient area will survive to ensure
468 long-term population persistence. There is also the question of which is the most appropriate
469 resolution to model at for any given species. This will vary among species depending on the
470 movement rates of individuals and the area required to support populations. Where such data
471 do exist, individual-based mechanistic models (rather than the correlative ones used here)
472 may be more appropriate as they provide a dynamic response to change based on well
473 understood processes (e.g. Clark *et al.*, 2001; Wallentin *et al.*, 2008). However, for the vast
474 majority of species (as for the example species modelled in this study), such data do not exist.
475 In these cases, comparing results from a range of resolutions to give a range of values for

476 predicted suitability of landscapes is a step forward in representing the needs of the species
477 more accurately.

478

479 A challenge is the need for high resolution analyses over large spatial extents, and a more
480 systematic approach to sampling would be beneficial (Eyre *et al.*, 2005). To date, studies
481 (including ours) often focus on relatively small geographical extents when modelling at a fine
482 resolution. This is because it is impractical to collect distribution data at the fine resolution
483 required for such studies throughout the whole of a species' range. However, the approach
484 that we advocate may become increasingly feasible because: (a) as in this study, one only
485 needs data from a sample of precisely georeferenced locations (it is not necessary to cover
486 every cell); (b) many existing records are already at 100 m grid resolution
487 (<http://data.nbn.org.uk>); and (c) cheap GPS units mean that many records are now submitted
488 with location data that have a precision of < 20 m. Such records could be used to model
489 species distributions at a fine resolution across whole countries in order to make a fair
490 comparison between coarse and fine resolution models across large geographical extents.
491 These models would then give conservation managers a better idea of the priority areas that
492 should be managed for species of interest, both within single sites and on a national and
493 international basis.

494

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496

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677

678 **Supporting Information**

679 Table S1: Correlation coefficients between temperature variables

680 Table S2: Variable coefficients for *C. glabratus*, where T_{mean} has been removed

681 Table S3: Variable coefficients for *P. versicolor*, where T_{mean} has been removed

682 Table S4: Variables included in the best model selected by MMI for *C. glabratus*

683 Table S5: Variables included in the best model selected by MMI for *P. versicolor*

684 Table S6: Variables included in the best model selected by backwards stepwise regression on

685 AIC for *C. glabratus*

686 Table S7: Variables included in the best model selected by backwards stepwise regression on

687 AIC for *P. versicolor*

688 Figure S1: Model predictions for *C. glabratus* based on models in Table S2

689 Figure S2: Model predictions for *P. versicolor* based on models in Table S3

690 Figure S3: Model predictions for *C. glabratus* based on models in Table S4

691 Figure S4: Model predictions for *P. versicolor* based on models in Table S5

692 Figure S5: Model predictions for *C. glabratus* based on models in Table S6

693 Figure S6: Model predictions for *P. versicolor* based on models in Table S7

694

695 **Biosketch**

696

697 **Phillipa Gillingham** is interested in the ecology and conservation of upland ecosystems, as

698 well as the effects of climate change on the distributions of species and how this will affect

699 conservation in the future. She is currently based at Bournemouth University, where she is a
700 lecturer in Biogeography. Author contributions: PKG and CDT conceived the idea with
701 advice from BH and WEK. PKG collected and analysed the data with advice from CDT, BH
702 and WEK. PKG led the writing, CDT, BH and WEK made extensive comments on all drafts.
703

704 Table 1: Summary of the Generalised Linear Models fitted at each resolution (Res), with number of sample locations N. Shown are the β -
705 coefficient of the relationship between abundance of *Carabus glabratus* and annual mean temperature (βT_{mean}), winter minimum temperature (β
706 T_{min}) and summer maximum temperature (βT_{max}) with standard errors in brackets, along with their associated p-values. A + in the Effort column
707 indicates that the log trapping effort was included as an offset in the model. Delta AIC of the best model and prediction error (PE) are also
708 shown.

709

710	Res	N	Effort	βT_{mean}	p	βT_{min}	p	βT_{max}	p	DeltaAIC	PE
711	5	40	+	-	-	-	-	-0.91 (0.23)	<0.0001	-11.09	143.83
712	100	40	+	-1.21 (0.71)	0.0879	-	-	-	-	-3.21	176.65
713	200	40	+	-	-	-	-	-1.05 (0.25)	<0.0001	-12.62	157.53
714	300	36	+	-	-	-	-	-1.17 (0.26)	<0.0001	-12.50	202.42
715	400	34	+	0.84 (0.90)	ns	-	-	-0.57 (0.31)	0.0709	-2.17	212.20
716	500	30	+	-	-	1.08 (0.83)	ns	-0.59 (0.27)	0.0296	-5.54	110.98
717	600	28	+	-	-	-	-	-0.92 (0.43)	0.0338	-2.21	366.30
718	700	25	+	-1.63 (0.98)	0.0950	-	-	-	-	-6.86	501.38
719	800	22	+	-0.82 (0.87)	ns	-	-	-	-	-3.22	532.21
720	900	20	+	-	-	-	-	-0.76 (0.40)	0.0608	-7.84	296.40
721	1000	20	+	-	-	0.07 (1.12)	ns	-	-	-3.12	530.38
722											

723 Table 2: Summary of the Generalised Linear Models fitted at each resolution (Res), with number of sample locations N. Shown are the β -
724 coefficient of the relationship between abundance of *Poecilus versicolor* and annual mean temperature (βT_{mean}), winter minimum temperature (β
725 T_{min}) and summer maximum temperature (βT_{max}) with standard errors in brackets, along with their associated p-values. A + in the Effort column
726 indicates that the log trapping effort was included as an offset in the model. Delta AIC of the best model and prediction error (PE) are also
727 shown.

728

729

730	Res	N	Effort	βT_{mean}	p	βT_{min}	p	βT_{max}	p	DeltaAIC	PE
731	5	40	+	4.44 (0.71)	<0.0001	-	-	-	-	-24.54	25.58
732	100	40	+	-	-	-	-	1.44 (0.44)	0.0012	-8.61	32.59
733	200	40	+	4.34 (0.82)	<0.0001	-	-	-	-	-19.38	30.54
734	300	36	+	-	-	4.30 (0.93)	<0.0001	0.60 (0.31)	0.0494	-15.98	25.43
735	400	34	+	4.06 (1.12)	0.0003	-	-	-	-	-10.07	39.23
736	500	30	+	4.29 (1.29)	0.0008	-	-	0.41 (0.46)	ns	-16.24	47.25
737	600	28	+	5.34 (1.83)	0.0035	-	-	-	-	-11.96	63.09
738	700	25	+	-	-	2.54 (1.78)	ns	1.65 (0.64)	0.0096	-7.65	9.99
739	800	22	+	4.25 (1.28)	0.0009	-	-	-	-	-9.67	60.18
740	900	20	+	3.57 (2.18)	ns	-	-	-	-	-3.28	93.82
741	1000	20	+	-	-	40.60 (1.59)	0.0038	-	-	-13.42	82.55

742 **Figure legends**

743 Figure 1: Locations within the landscape that were sampled for *Carabus glabratus*. Presences
744 (black circles) and Absences (white circles) are shown on a 1 km resolution grid of cells with
745 presence only (dark grey), absence only (pale grey) and containing both presence and absence
746 records (mid grey)

747

748 Figure 2: The maximum temperature in July 2008 (T_{max}) across the Lake Vyrnwy field site,
749 shown at four different resolutions a) 5 m b) 100 m c) 500 m d) 1000 m

750

751 Figure 3: The relationship between input data resolution and perception of various parameters
752 at 2008 conditions; a) the maximum of T_{max} (black squares), minimum of T_{max} (black
753 triangles), maximum of T_{mean} (grey squares), minimum of T_{mean} (grey triangles), maximum of
754 T_{min} (open squares) and minimum of T_{min} (open triangles) in the landscape.

755

756 Figure 4: The proportion of the landscape predicted to remain thermally suitable for *Carabus*
757 *glabratus* following climate warming based on the model with the lowest prediction error.
758 Each line represents a different resolution model.

759

760 Figure 5: The proportion of the landscape predicted to become thermally suitable for *Poecilus*
761 *versicolor* following climate warming based on the model with the lowest prediction error.
762 Each line represents a different resolution model.

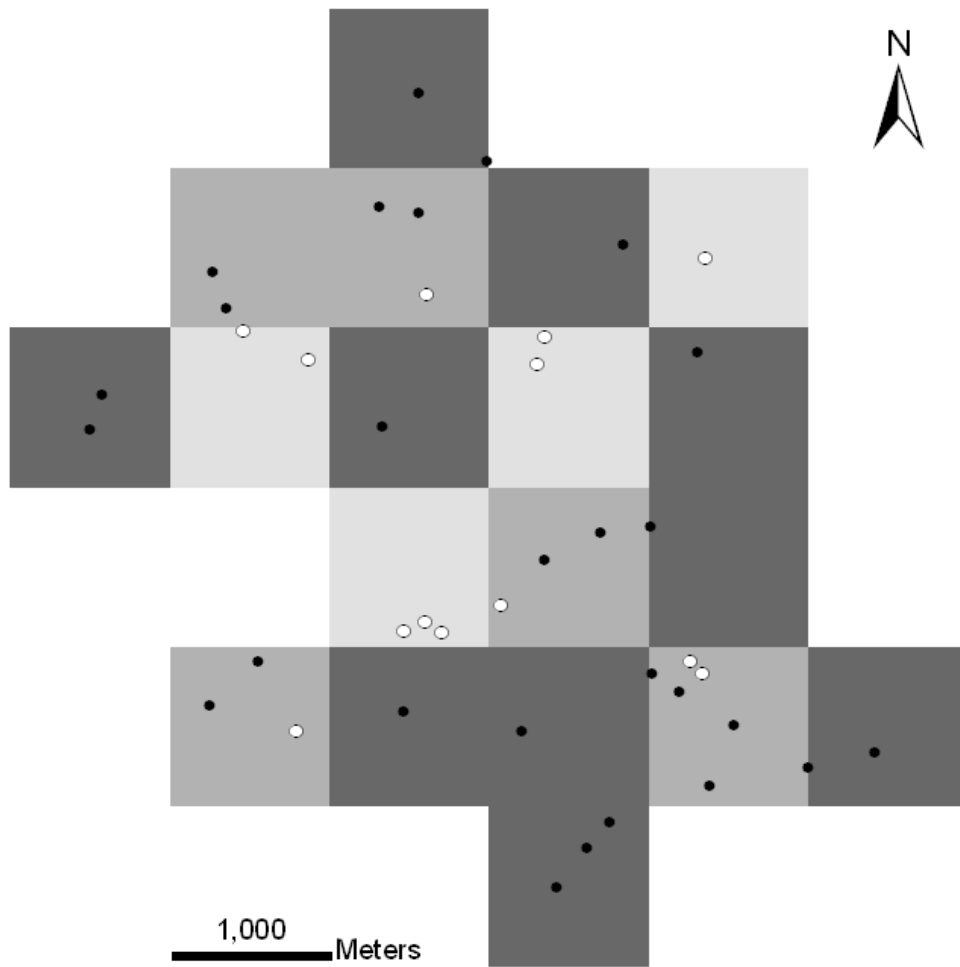
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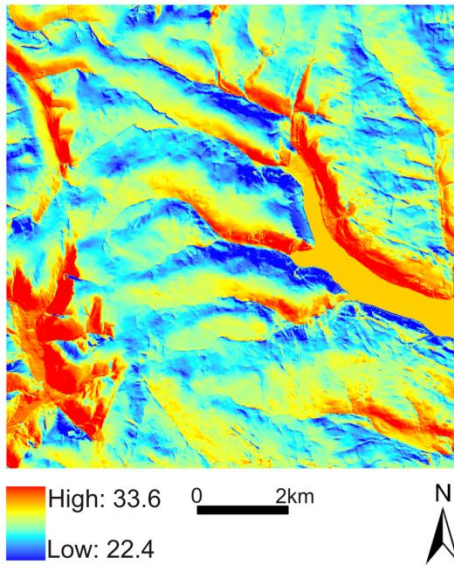
767 **Figure 1:**



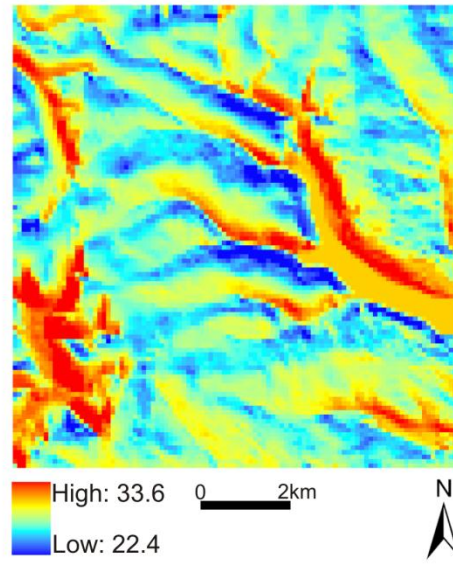
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770 **Figure 2:**
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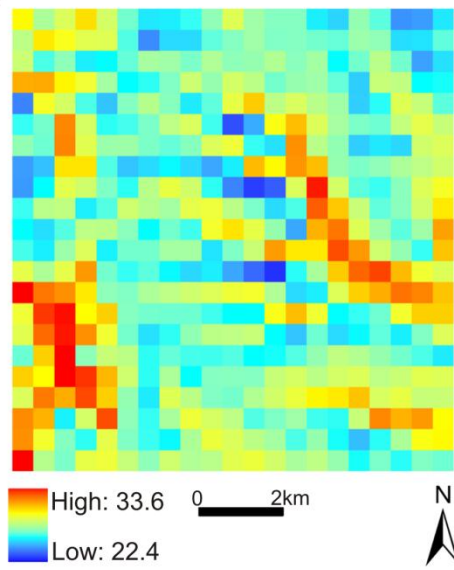
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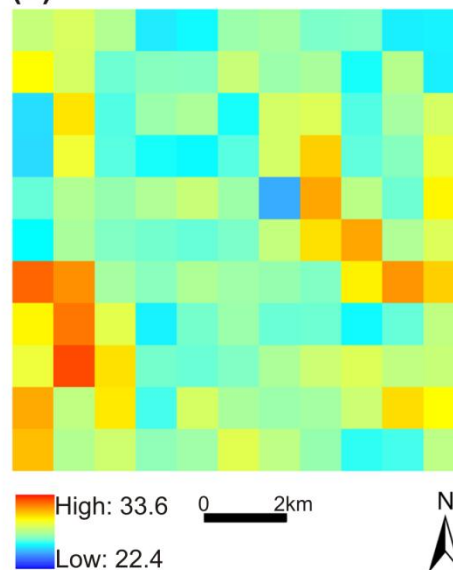
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(c)



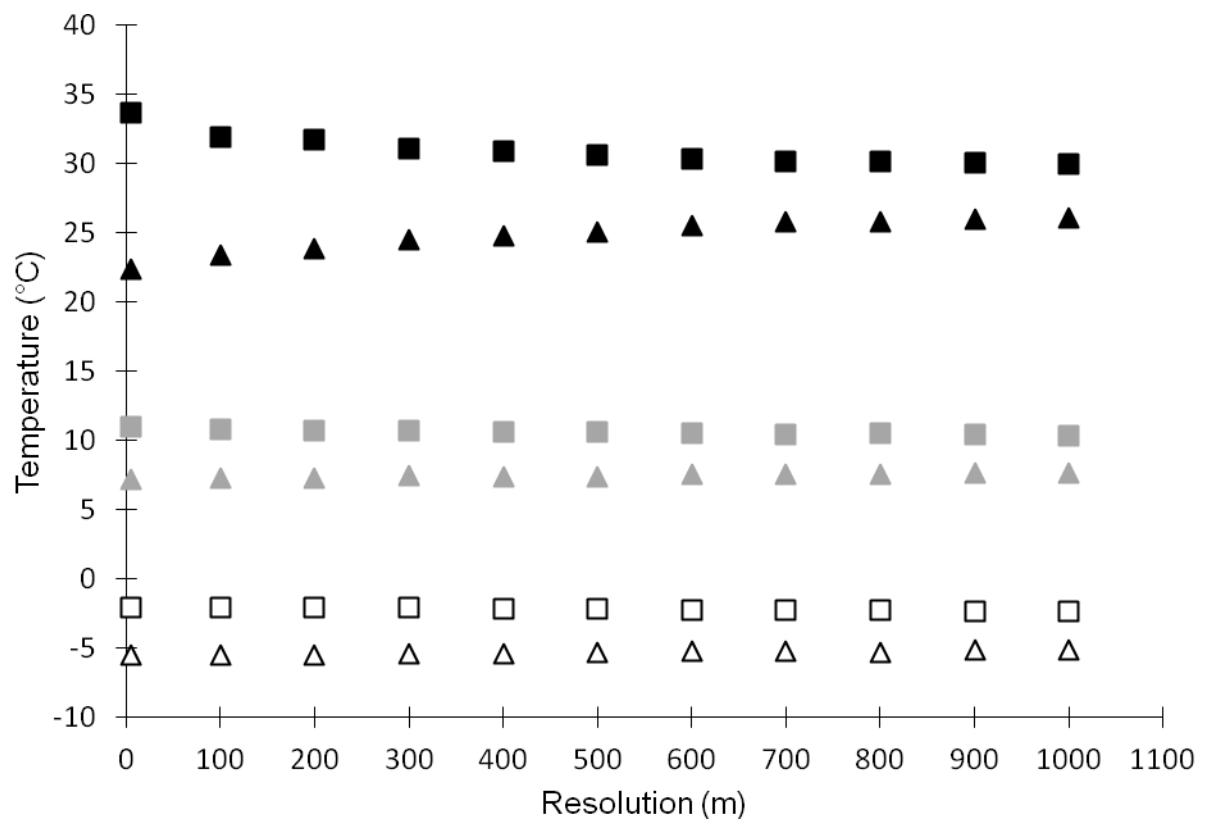
(d)



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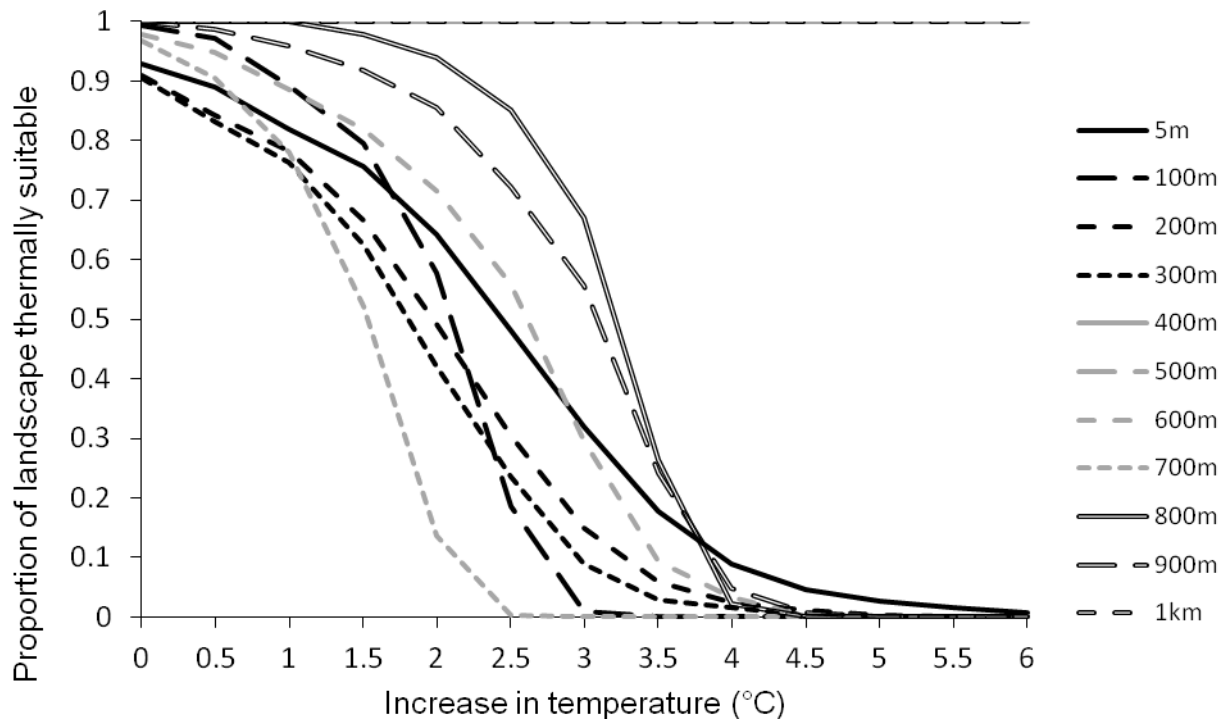
775 **Figure 3:**



776

777 **Figure 4:**

778



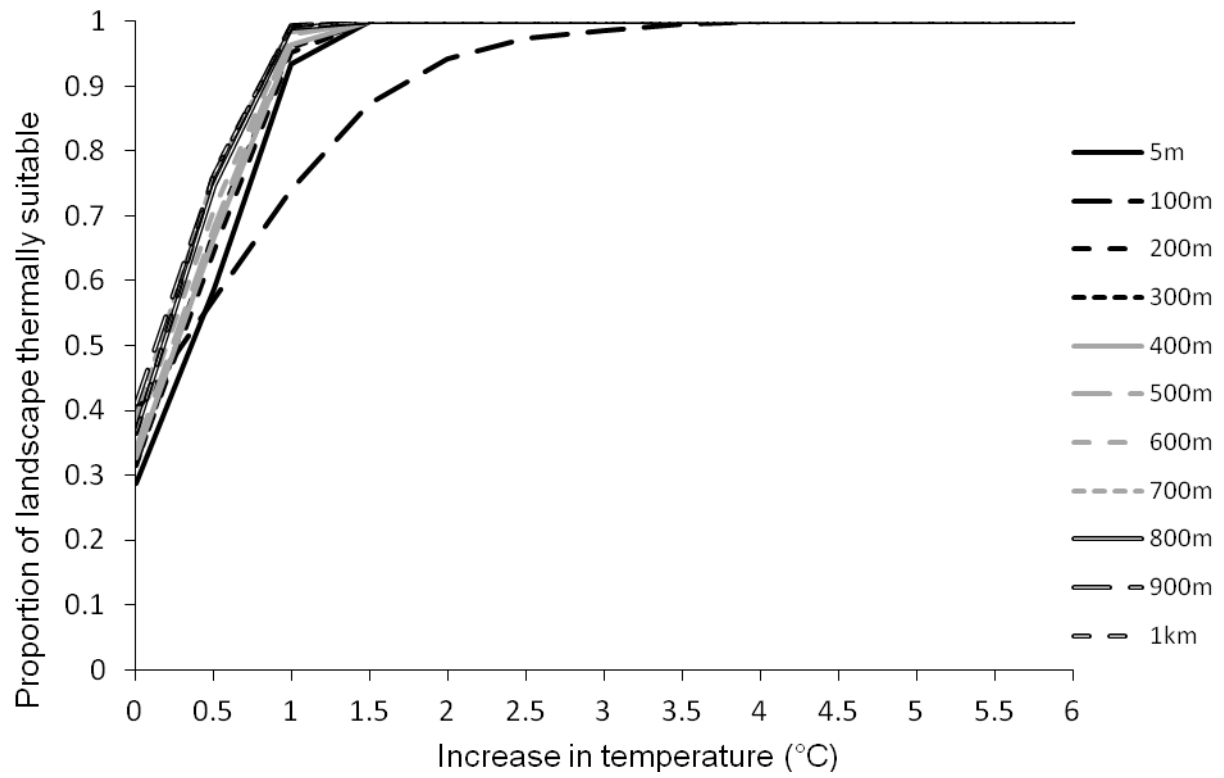
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781 **Figure 5:**

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784