

1 **Improving forecasts of arctic-alpine refugia persistence with landscape-scale variables**

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7 Niskanen A.K.J., Heikkinen R.K., Mod H.K. and Luoto M., 20xx.. Improving forecasts of arctic-alpine refugia
8 persistence with landscape-scale variables. *Geografiska Annaler, Series A: Physical Geography*.

9 **ABSTRACT**

10 Refugia, sites preserving conditions reminiscent of suitable climates, are projected to be crucial for species in a changing
11 climate, particularly at high latitudes. However, the knowledge of current locations of high-latitude refugia and
12 particularly their ability to retain suitable conditions under future climatic changes is limited. Occurrences of refugia have
13 previously been mainly assessed and modelled based solely on climatic features, with insufficient attention being paid to
14 potentially important landscape-scale factors. Here, climate-only models and ‘full’ models incorporating topo-edaphic
15 landscape-scale variables (radiation, soil moisture and calcareousness) were developed and compared for 111 arctic-
16 alpine plant species in Northern Fennoscandia. This was done for both current and future climates to determine cells with
17 resilient climatic suitability harbouring refugia. Our results show that topographic and edaphic landscape-scale predictors
18 both significantly improve models of arctic-alpine species distributions and alter projections of refugia occurrence.
19 Predictions of species-climate models ignore landscape-scale ecological processes and may thus provide inaccurate
20 estimates of extinction risk and forecasts of refugia where species can persist under a changing climate.

21 *Keywords:* climate change; refugia; landscape-scale factor

22 **Introduction**

23 Previous research has shown the importance of refugia for species survival during past environmental changes (Taberlet,
24 1998; Birks & Willis, 2008; Svenning *et al.*, 2008). Refugia are sites that provide environmental conditions deviant from
25 the regional average, thereby supporting species persistence in a changing climate (Médail & Diadema, 2009; Keppel *et*
26 *al.*, 2012). Due to the rate and magnitude of global change, refugia are also likely to be among the major mechanisms
27 assisting species persistence in the future (Reside *et al.*, 2013) and should thus be acknowledged in climate change–based
28 conservation planning. A challenge still remains in the credible identification of present-day refugia across landscapes,
29 and particularly in assessing their capability to retain suitable conditions under future climatic changes. Spatial

30 information regarding future refugia is particularly important at high latitudes, as they are among the most susceptible
31 environments to a changing climate (Root *et al.*, 2003; Ashcroft, 2010). However, little is known about which high-
32 latitude landscapes and species are most vulnerable to projected future climatic trends. This knowledge gap calls for
33 increased attention on robust forecasts of how the suitable areas for the species might change, which environmental factors
34 are most critical for developing the most reliable models of this change, and how well potential future refugia are
35 discernible from a given landscape.

36 Species distribution models (SDMs) are a commonly used tool to forecast the spatial changes in realized
37 or potential species distributions (Guisan & Thuiller, 2005; Araújo & Peterson, 2012). SDMs have also been shown to
38 complement and be spatially correlated with traditionally used phylogeographic estimates of past refugia distribution
39 while providing less subjective and spatially more explicit predictions (Waltari *et al.*, 2007). However, it is increasingly
40 recognized that SDMs often require both climatic variables and non-climatic variables describing landscape-scale or local
41 environmental conditions to maximize predictive ability (Franklin, 1995; Austin & Van Niel, 2011a; Beauregard & de
42 Blois, 2014). Such integrative modelling studies have not, however, been carried out for arctic-alpine species or their
43 refugia in high-latitude regions. This is a shortcoming as the inclusion of landscape-scale factors into SDMs developed
44 for high-latitude refugia may be of particular significance and help identify locations able to preserve environmental
45 conditions reminiscent of the current climate within the surrounding changing matrix, thus leading to more robust
46 predictions of future refugia (Austin & Van Niel, 2011a; Hodd *et al.*, 2014).

47 A frequently applied paradigm in the study of global change impacts on biota involves models of the
48 distributional changes of species – or the areas environmentally suitable for them - as spatially explicit functions of
49 projected change (Guisan & Thuiller, 2005; Botkin *et al.*, 2007). Similarly, previous studies using spatial models of
50 predicted species distributions have mainly approached refugia from the viewpoint of a single species (Hugall *et al.*, 2002;
51 Austin & Van Niel, 2011a), past distributions (Fløjgaard *et al.*, 2009) or coarser spatial scales (Hodd *et al.*, 2014). Here,
52 we investigate whether the addition of landscape-scale variables to climate-only SDMs (1) leads to different
53 interpretations of how projected changes in climate may affect the distributions of 111 arctic-alpine plant species, and (2)
54 modifies predictions of in situ refugia for these species in N-Fennoscandia. We base these analyses on high-quality species
55 and environmental data, and predict species distributions under contemporary climate as well as two projected future
56 climates i.e. Representative Concentration Pathway (RCP) scenarios: the moderate RCP 4.5 (Smith & Wigley, 2006;
57 Clarke *et al.*, 2007; Wise *et al.*, 2009) and extreme RCP 8.5 scenarios (Riahi *et al.*, 2007).

58 **Materials and methods**

59 *Study area*

60 Located in Northern Fennoscandia between 67°N and 70°N, the sub-arctic climate of our study region is driven by its
61 position at the edge of the Eurasian continent, the Polar Front, the warm North Atlantic current, and proximity to the
62 Scandes Mountains (Fig. 1) (Tikkanen, 2005; Aalto *et al.*, 2014b). The area is characterized by varying climatic,
63 topographic and geologic gradients (Oksanen & Virtanen, 1995). Average July temperatures range from 6.1 °C to 15.2 °C
64 and mean annual precipitation from 449 mm to 600 mm (1981 – 2010 means) (Pirinen *et al.*, 2012). Elevation ranges
65 from 72 to 1365 m.a.s.l. The vegetation gradient varies from spruce (*Picea abies*) and Scots pine (*Pinus sylvestris*) forests
66 in the south to mountain birch (*Betula pubescens* subsp. *czerepanovii*) in the north, with shrub-dominated tundra-like
67 vegetation above the tree-line (Sormunen *et al.*, 2011).

68 Preliminary data analysis indicated that parts of our study area are predicted to have a future climate with
69 no current equivalent within the study region. To reduce errors from predicting species responses to climatic conditions
70 without current equivalents, and as arctic-alpine species are generally expected to move northwards as the climate warms,
71 we used data from the whole area for training the models, but excluded the non-analogue southern- and easternmost
72 regions of our study area from model projections (dashed line in Fig. 1) (Sætersdal *et al.*, 1998; Heikkinen *et al.*, 2006).

73 *Species data*

74 Species occurrence data for 1341 1 km² cells were collected by botanists and volunteers, and refined using scientific
75 literature and herbaria. The sampling cells cover all important vegetation zones and ecosystems present in the study area,
76 ranging from taiga to treeless tundra (Kurtto & Lampinen, 1999). Only arctic-alpine species (defined according to
77 biogeographic distribution by professional botanists; see le Roux *et al.* (2012)) with an occurrence in a minimum of eight
78 cells within our study area were included in the subsequent analysis ($n=111$).

79 *Selection of predictors*

80 We used an extensive grid of environmental data matching the resolution of the species data (1 km²) to investigate key
81 refugia predictors. We chose to demonstrate our methodology using a set of climate and landscape-scale terrain and
82 geological variables (Table 1) known to be important for plant species (Skov & Svenning, 2004; Austin & Van Niel,
83 2011a; Dobrowski, 2011; Scherrer & Körner, 2011). The chosen direct and resource variable predictors (Austin & Smith,
84 1990) represent growing conditions, surface temperature, light, moisture and soil conditions considered critical for high-
85 latitude vegetation.

86 The climate data, comprising of observations from 61 stations in Northern Fennoscandia, were acquired
87 from the national observation networks of Finland (Finnish Meteorological Institute), Sweden (Swedish Meteorological
88 and Hydrological Institute) and Norway (Norwegian Meteorological Institute), and modelled to a 1 km² resolution grid
89 (see Aalto *et al.*, 2014). Three climatic predictors with a temporal coverage of 1981–2010 were initially included in the
90 analyses: growing degree days (GDD3; annual accumulated daily temperature sum above 3°C, i.e. growing conditions),
91 temperature of the coldest quarter (TCQ; overwintering conditions) and water balance (WAB; moisture conditions).
92 However, due to ecologically erroneous projections resulting from the counter effects of different climatic variables
93 caused by variable multicollinearity, (namely strong correlations of GDD3 with TCQ and WAB [Spearman's rank
94 correlation coefficients, $r_s = -0.88$ and $r_s = -0.87$, respectively]), only GDD3, which correlates the most with arctic-alpine
95 species diversity in the study area ($r_s = -0.75$), was ultimately included in the final models.

96 Landscape features exert a strong influence through numerous geomorphological, hydrological,
97 geological and biological processes (Moore *et al.*, 1991), thus controlling the growing conditions experienced by plants
98 (Guisan *et al.*, 1998; Ackerly *et al.*, 2010; Scherrer & Körner, 2011). Here, three topo-edaphic landscape-scale predictors
99 were used: (1) incoming potential solar *radiation* representing surface temperature conditions (McCune & Keon, 2002);
100 (2) digital elevation model-derived topographic wetness index (*TWI*) representing the availability of soil moisture from
101 upslope areas (Beven & Kirkby, 1979); and (3) *calcareousness* representing the proportion of calcareous, nutrient-rich
102 bedrock in a given 1 km² grid cell (Dubuis *et al.*, 2013). In contrast to GDD3, the relative effects of radiation, fluvial
103 processes (e.g. *TWI*) and soil properties (e.g. *calcareousness*) should remain more constant in the future (Reside *et al.*,
104 2013). Radiation and *TWI* were based on an Aster -derived digital elevation model (NASA Land Processes Distributed
105 Active Archive Center (2013); spatial resolution 30 m²). Radiation was calculated using the ArcView 3.2 Solar analyst
106 extension which uses digital elevation models to generate radiation data by accounting for latitude, elevation, slope angle,
107 slope aspect, shadows cast by surrounding topography, daily and seasonal shifts in solar angle, and atmospheric
108 attenuation (Fu & Rich, 1999). Due to the landscape scale of this study, only one latitude value (here, 69°) for the whole
109 digital elevation model was used. *TWI*, the most often used surrogate for soil moisture, was calculated using a Python
110 script written by Prasad Pathak that accounts for slope and local upslope contributing area (Beven & Kirkby, 1979; Esri,
111 2013). *Calcareousness* was reclassified from a digital database (Geological Survey of Finland 2010; spatial resolution 20
112 m²). The landscape predictors were resampled by spatial averaging to a 1 km² resolution to match the species and climate
113 data.

114

Climate change scenarios

115 Forecasts for the locations of refugia may vary between climate scenarios, thus making it imperative to consider
116 predictions based on multiple scenarios (Reside *et al.*, 2013). Four sets of scenarios containing different emission,
117 concentration and land-use trajectories, have been developed (Van Vuuren *et al.*, 2011). These scenario sets are referred
118 to as Representative Concentration Pathways (RCPs) and they correspond to different greenhouse gas (GHG)
119 concentration trajectories (Moss *et al.*, 2010). Here we explore the implications of two possible future pathways, RCP 4.5
120 and RCP 8.5 (where the number refers to radiative forcing in watts/m² by the year 2100). RCP 4.5 is an intermediate
121 mitigation scenario where GHG emissions are stabilized at low to medium levels (Van Vuuren *et al.*, 2011). RCP 8.5, the
122 unabated ‘business-as-usual’ scenario, represents the highest GHG emission profile (Riahi *et al.*, 2011; Van Vuuren *et*
123 *al.*, 2011).

124

Statistical analyses

125 Observed species distributions were related to the set of predictors using five statistical modelling techniques. These
126 included two regression methods: generalized linear modeling (GLM) (McCullagh & Nelder, 1989) and generalized
127 additive modeling (GAM) (Hastie & Tibshirani, 1990) and three machine-learning methods: generalized boosting
128 methods (GBM, also known as boosted regression trees (BRT)) (Elith *et al.*, 2008), random forest (RF) (Breiman, 2001)
129 and maximum entropy (MAXENT) (Phillips *et al.*, 2004). All the models were implemented in the Biomod2 platform
130 (Thuiller *et al.*, 2013) using R-program (R Development Core Team 2013). The models were fitted using two sets of
131 predictors:

132

$$\text{Occurrence of species} = \text{GDD3}$$

133

[base model]

134

$$\text{Occurrence of species} = \text{GDD3} + \text{CALC} + \text{RAD} + \text{TWI}$$

135

[full model]

136 Model transferability was assessed using four-fold cross-validation. We applied a commonly used approach
137 (Zimmermann *et al.*, 2009; le Roux *et al.*, 2013b; Aalto & Luoto, 2014) to compare the predictive power of base (climate-
138 only) and full (climate-plus-landscape) models by calculating the area under the curve of a receiver operating
139 characteristic (AUC) plot (Fielding & Bell, 1997), true skill statistics (TSS) and Cohen’s Kappa coefficient (Allouche *et*
140 *al.*, 2006) based on the four evaluation runs (where the models calibrated with 75% of the data were evaluated with the
141 withheld 25 % of the data, and repeated for each of the four quarters of the data). A non-parametric Wilcoxon’s test was
142 employed to examine whether explanatory power and predictive accuracy differed significantly between models.

143 All data were used for projecting species occurrences to current and future climatic conditions.
144 Occurrence probabilities were transformed to binary presence/absence predictions using a TSS cutoff, maximizing model
145 accuracy, defined by BioMod2. In order to account for intermodal variability and to create the final maps of predicted
146 species distributions, we used the consensus approach (Araújo & New, 2007) to construct an ensemble of forecasts that
147 combine the binary predictions from all models. Here we chose a majority's vote of a minimum of three out of five
148 modelling techniques to denote a presence value for a given species inside a given 1 km² grid cell (Figure S1).

149 For each species, variable influence was assessed in Biomod2 by randomizing each variable individually
150 and then projecting the model with the randomized variable while keeping the other variables unchanged. The model
151 predictions containing the randomized variable were then correlated with those of the original models. Finally, the
152 importance of the variable was calculated as one minus the correlation, with higher values indicating higher predictor
153 importance (Thuiller *et al.*, 2009). This was repeated ten times for each modelling method and the resulting variable
154 influence values were averaged.

155 Definition of refugia

156 Areas where the contemporary and future distributions of species overlap may act as refugia (Temunović *et al.*, 2013).
157 By modelling contemporary and projected climates, we can identify these spatiotemporal species distribution overlaps
158 (henceforth referred to as 'resilient cells'). Here, we regard these resilient cells as potential sites for *in situ* refugia where
159 local species may be maintained, i.e. persist even under the assumption of no dispersal (Thomas *et al.*, 2004; Pearson,
160 2006). *In situ* refugia are more likely to function as effective refugia as reaching them requires only local or no range-
161 shifts (Reside *et al.*, 2014) and, by remaining within the present range of a given species, they provide a robust estimate
162 of species persistence (Shoo *et al.*, 2013).

163 To locate *in situ* refugia from SDM predictions we utilized a step-by-step approach as follows (Figure
164 S1): firstly, as refugia are essentially species-specific (Provan & Bennett, 2008; Stewart *et al.*, 2010), we model the species
165 separately to gain insights into their preferred environments. Next, the single-species predictions are projected separately
166 into current climatic conditions and two future climate scenarios to locate cells where species occurrence is maintained
167 both spatially and temporally (Shoo *et al.*, 2013; Temunović *et al.*, 2013). Finally, as favourable environmental conditions
168 supporting refugia may overlap for several species (Hampe & Petit, 2005; Keppel *et al.*, 2012) and to increase prediction
169 robustness, we stack projections of these resilient cells to locate sites where suitable conditions persist for several species.
170 Areas with higher arctic-alpine species diversity are strong refugia candidates as they maximize available information
171 and the probability of this diversity persisting under climate change. Consequently, sites harbouring several refugial

172 species simultaneously are potentially very valuable for future conservation planning. Thus, we set a threshold of a
173 minimum of five persisting species as a prerequisite for a resilient 1 km² grid cell to be classified as a refugia.

174 **Results**

175 The use of topo-edaphic landscape-scale predictors significantly ($p < 0.001$) improves the accuracy of SDMs developed
176 for the studied arctic-alpine species. Based on the cross-validation runs, the mean AUC values improved from 0.77 (base
177 i.e. climate-only model) to 0.86 (full i.e. climate-plus-landscape model). The corresponding TSS values improved from
178 0.51 to 0.62, and Kappa values from 0.39 to 0.46 (Table 2). Lower standard deviations of the evaluation metrics in the
179 full models also indicate greater model accuracy (Table 2).

180 The inclusion of landscape-scale predictors changes contemporary predictions of refugia as well as
181 projections of species distributions and predictions of the availability of suitable environments for arctic-alpine species
182 in a warming climate. Differences arise in both predictions of how many species are predicted to persist in a given refugia,
183 as well as the total count i.e. spatial extent of refugial cells. The full model predicts fewer species range reductions and
184 higher species persistence (Fig 2: b, d; Table S1): out of the 111 species, the full model locates refugia for 77 species in
185 RCP 4.5 (climate-only model: 40 species) and 47 species in RCP 8.5. Considerably less refugia were predicted by the full
186 model into the more extreme RCP 8.5 (207 refugia; compared to 959 in RCP 4.5; Table S1). The base model does not
187 project any refugia into RCP 8.5 (Fig 2: c). The spatial extent of refugial cells predicted by both models into RCP 4.5
188 shows a 79% overlap (Fig 2: a, b). However, over 95% of the refugial cells predicted by the full model for RCP 4.5
189 demonstrate a higher species persistence rate than predictions from the base model (Fig 2: b, d; Table S1).

190 Out of the 111 species included in the analysis, GDD3 was the most influential variable for most of the
191 species ($n=69$); calcareousness for 26 species; TWI for 13 species; and radiation was the most important variable for three
192 species. An example of projected refugia for Alpine Mouse-ear (*Cerastium alpinum*) are shown in Figure S3. This small
193 perennial herb shows a clear preference for high substrate calcareousness and cooler growing conditions offered by the
194 regions refugia. There is a clear spatial prominence of refugial cells around the cooler, more calcareous mountainous
195 regions of the study area (Figs 1 & 2; Table S2; Figure S4: b-d). By including topo-edaphic landscape-scale variables,
196 suitable environments for arctic-alpine species can, however, be projected into cells with a higher GDD3 than by
197 accounting for climate alone. Aside from climatic differences, the refugia derived from full model predictions also exhibit
198 slightly differing landscape conditions, here higher radiation, a higher cover of calcareous substrates and lower TWI
199 (Table S2).

200 **Discussion**

201 Our results demonstrate more detailed and accurate predictions of refugia following the inclusion of landscape-scale
202 variables reflecting the topo-edaphic conditions to climate-only models. This is due to the limiting effect of using only
203 climatic predictors that overlooks certain fine-resolution spatial and temporal (e.g. extent and persistence of suitable
204 habitat, respectively) aspects of species distributions. In other words, consideration of landscape properties is required to
205 capture the important topo-edaphic conditions shaping refugia distribution patterns in space and time (Austin & Van Niel,
206 2011b), and our study shows that this is true also for high-latitude environments.

207 Refugia defined using both climate and topo-edaphic parameters, compared to refugia defined by climate
208 alone, are more likely to continue to provide suitable conditions for a greater portion of arctic-alpine species growing in
209 a given grid cell (Dobrowski, 2011; Keppel *et al.*, 2012). The inclusion of topo-edaphic variables modifies climate-only
210 models in a way that enables predictions of suitable future conditions into a number of cells with warmer average growing
211 conditions. This significance of accounting for the topo-edaphic setting results partly from how it can modify the climatic
212 conditions experienced by species (Austin & Van Niel, 2011a; Lenoir *et al.*, 2013). As seen for the example species,
213 Alpine Mouse-ear, the climate-only model predicts species persistence in northern refugia, where temperatures are cooler
214 (Figs S2 & S4). The refugia show a more spatially dispersed pattern of persistence in a changed climate, but the forecasts
215 of species persistence are made more optimistic through additions of topographic and edaphic predictors. Moreover,
216 improvements to the models and derived predictions resulting from the incorporation of landscape-scale variables also
217 emphasize an increase in species' tolerance in confronting climatic changes via edaphic conditions (Table S2; Fig S3).
218 The importance of calcareous substrate also shows that adjusting climate models with topographical variables only, e.g.
219 constructing topoclimatic models, may lead to misrepresentative conclusions regarding SDMs and climate change
220 predictions.

221 Possibly owing to the importance of climate as a predictor, the spatial distribution of refugia appears
222 similar between the base and full model predictions for RCP 4.5. This is particularly evident in the northern regions of
223 the study area where GDD3 levels remain favourably low for arctic-alpine species persistence. Areas with the least
224 environmental change are more likely refugia candidates for most species within a grid cell (Reside *et al.*, 2013) and,
225 indeed, considerably less refugia were predicted by the full model into the more extreme RCP 8.5 (207 refugia; compared
226 to 959 in RCP 4.5). The spatial distribution of these 207 refugial cells is more dispersed, suggesting that refugial species
227 in a warmer future would need to rely on more isolated habitats to provide locally favourable landscapes. Though
228 decreased by climatic changes, forecasts of species persistence in refugia are improved by even fairly simple topo-edaphic
229 landscape properties at the mesoscale. Examining such grid cells where species can persist is a robust way of mapping

230 distributional changes and refugia, though dispersal abilities and possible time lags of species responses to changing
231 landscape configurations are also likely to contribute to the effectiveness of refugia. However, accounting for
232 circumstances of little or no spatial overlap between current and future suitable environments would require information
233 on species dispersal capacities (Reside *et al.*, 2013; Reside *et al.*, 2014) to *ex situ* refugia (Shoo *et al.*, 2013) to enable
234 more realistic estimates of species range-shift abilities to future refugia.

235 The distributions of a majority of the 111 arctic-alpine species studied here are projected to shrink
236 following increases in temperature with most of the study region appearing as a matrix of unsuitable growing conditions
237 for arctic-alpine species. Heterogeneous mountainous regions, such as the northern areas of our study landscape, are
238 expected to be exceedingly important for refugia and the conservation of species (Loarie *et al.*, 2008; Luoto & Heikkinen,
239 2008; Scherrer & Körner, 2011), especially for endemic mountain plants at risk from range reduction by upward
240 displacement (Rull & Vegas-Vilarrúbia, 2006). Indeed, our finding that the located refugia are offering conditions of
241 lower soil moisture (as indicated by the variable TWI) is related to the assumption that steeper slopes, such as those found
242 in the Scandes, are less likely to retain water (Beven & Kirkby, 1979). The significance of these mountain refugia,
243 however, is likely to be affected by species' properties such as growth form and dispersal capacity (Engler *et al.*, 2009),
244 and mountain refugia have been disputed to be of little avail to small, scattered populations of species (Birks, 2008). The
245 reduction in available land area at higher elevations may also result in species' local extinctions (Patsiou *et al.*, 2014).
246 Nevertheless, the *in situ* refugial expanse in the mountainous area of the study region is projected to be an important
247 location for providing many arctic-alpine species with suitable conditions for persistence, and its potential to do so
248 deserves further investigation.

249 More generally, it needs to be acknowledged that evaluating the capability of refugia in promoting species
250 persistence and ecosystem resilience is difficult due to the many uncertainties involved in predicting and modelling
251 climate, changes therein, and species responses to these changes (Wiens *et al.*, 2009; Reside *et al.*, 2013; Shoo *et al.*,
252 2013). For example, assuming uniform warming across a given landscape, or basing forecasts of changes in local climate
253 on simple temperature-elevation correlations may over-emphasize the importance of relatively cool sites or higher
254 elevations (Ashcroft, 2010). Essential aspects of future refugia research include investigating the dynamics of climatic
255 decoupling between the atmosphere and terrain within arctic-alpine landscapes (Dobrowski, 2011; Scherrer & Körner,
256 2011; Hylander *et al.*, 2015), as we cannot surmise the effects of topography on climatic stability with the approach used
257 here. A similar modelling framework could also be used to pinpoint individual at-risk species, specific areas or habitat
258 types facing substantial changes in a warmer future (Thuiller *et al.*, 2005; Williams *et al.*, 2005; Loarie *et al.*, 2008).
259 Furthermore, though the landscape-scale predictors used here provide a solid basis for a comprehensive set of ecologically

260 meaningful predictors, enumerating the significance of other variables, such as geomorphological disturbances (Randin
261 *et al.*, 2009; le Roux *et al.*, 2013a; Slaton & Linder, 2015), CO₂ effects (Rickebusch *et al.*, 2008) and biotic interactions
262 (Godsoe *et al.*, 2015; Mod *et al.*, 2015), may also be necessary for more realistic predictions of refugia persistence (sensu
263 Austin and Van Niel 2011b), though their relevance is likely to be further pronounced at finer spatial scales. ur results,
264 highlighting the importance of topo-edaphic landscape-scale factors for modelling refugia as well as demonstrating
265 changes in the extent and connectivity of suitable habitat, show there is a strong case for applying a similar approach at
266 finer or even multiple scales to facilitate a more mechanistic approach to future refugia study.

267 **Conclusions**

268 Climate change projections suggest that returning to historical climatic conditions is highly improbable. Here we show
269 that, despite forecasted future regional warming, several resilient sites found in our study landscape are predicted to
270 maintain suitable local environments due to topo-edaphic conditions. Refugia can be found in places where locally
271 optimal environments remain constant across timescales and in which the effects of landscape preserve environmental
272 conditions more reminiscent of suitable contemporary climates. Predictions of species responses to climate change based
273 on climate alone may be inaccurate in estimating extinction risk as they neglect to consider topographic and edaphic
274 processes affecting species distributions, and may fail to identify refugia where species can persist. Thus, models of
275 species distributions and changes therein need to account for topo-edaphic landscape-scale variables to provide
276 information on relevant spatial and temporal responses to environmental change and should thus be explicitly accounted
277 for in future climate change impact assessment studies.

278 **Acknowledgements**

279 AN was funded by the Lapland Regional Fund (Finnish Cultural Foundation), Societas pro Fauna et Flora Fennica and
280 The Doctoral Program in Geosciences. We acknowledge funding from the Academy of Finland (Project Number
281 1140873). Also, HM was partly founded by the Alfred Kordelin Foundation and The Doctoral Program in Geosciences,
282 and ML was partly funded by the Academy of Finland (Project Number 286950). We would also like to thank the Finnish
283 Museum of Natural History as one of the main contributors of the data on vascular plant species and Juha Aalto for
284 helping with gathering the environmental data and data analysis.

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504 8.

507 **Table 1** Descriptions of the four focal environmental variables with their minimum (Min.), median (Med.), mean and
 508 maximum (Max.) values

Variable	Description	Min.	Med.	Mean	Max.
GDD3 (contemporary)	Growing degree days (annual accumulated daily temperature sum above 3°C; unit °C)	163	810	784	1050
(under RCP 4.5)		374	1247	1204	1489
(under RCP 8.5)		633	1620	1587	1964
Radiation	Potential annual direct radiation (MJ/cm ² /a)	0.28	0.43	0.43	0.62
TWI	Topographic wetness index	5.58	6.93	6.95	8.70
Calcareousness	Cover of calcareous substrates (%)	0	6.7	13.0	90.3

509

510 **Table 2** The model evaluation statistics for the base (climate-only) and full (climate-plus-landscape) models showing the
 511 mean and standard deviation (SD) of the evaluation metrics over four cross-validation runs. Wilcoxon signed rank test p-
 512 values show change in predictive ability (***) = highly significant). AUC improved for 104; TSS for 10; and Kappa for
 513 99 out of 111 species

	AUC		TSS		Kappa	
	Base	Full	Base	Full	Base	Full
Mean ± SD	0.77 ± 0.09	0.86 ± 0.06	0.51 ± 0.14	0.62 ± 0.13	0.39 ± 0.21	0.46 ± 0.16
p-value	< 0.001***		< 0.001***		< 0.001***	

514

515 **Fig 1.** The location and elevation of the study area in northern Fennoscandia. We used data from whole area for training
516 the models, but excluded non-analogue regions from the projections (white dashed line)

517

518 **Fig 2.** Refugia in two Representative Concentration Pathway (RCP) scenarios (RCP 4.5 a-b; RCP 8.5 c-d) of future
519 climate according to base models (climate-only; a, c) and full models (climate-plus-landscape; b, d). The full models
520 predict a higher relative species persistence from contemporary to future climates. No refugia were predicted for scenario
521 RCP 8.5 by the base model. The legend applies throughout

522 **Supporting Information**

523

524 **Figure S1:** An outline of the modelling framework used. We combined model predictions for 111 arctic-alpine plant
525 species to estimate current and projected species distribution and identify refugia at a 1 km² resolution. To enable the
526 comparison of species' distributional changes, we ran the predictions for contemporary climate as well as two
527 Representative Concentration Pathways (RCPs 4.5 and RCP 8.5). Two sets of predictors were used: climate-only
528 (growing degree days (GDD3)); and climate-plus-landscape, which included additional landscape-scale predictors:
529 potential solar radiation (RAD); calcareousness (CALC); and topographic wetness index (TWI). Observed species
530 distributions were related to the set of predictors using five statistical modelling techniques: generalized linear modeling
531 (GLM), generalized additive modeling (GAM), generalized boosting methods (GBM), random forest (RF) and maximum
532 entropy (MAXENT). All the models were implemented in the Biomod2 platform under R-program

533

534 **Table S1:** Summary statistics for arctic-alpine species persistence within refugia; the number (n) and proportion (%) of
535 species persisting in refugia according to the two model structures used and two scenarios of future climate. No refugia
536 were predicted for scenario RCP 8.5 by the base model. The total count of cells used in the analysis was 15 622

537

538 **Figure S2:** Predicted contemporary and future distributions of Alpine Mouse-ear (*Cerastium alpinum*) in the study area.
539 The predicted distributions were modelled into two scenarios of future climates (RCP 4.5 and RCP 8.5) according to two
540 sets of predictors: climate-only (base model) and climate-plus-landscape (full model)

541

542 **Figure S3:** Box-and-whisker plot showing the mean variable importance values based on the full model across all species
543 and across the five modelling techniques utilized (boxplot represents median, first and third quartiles; the whiskers show
544 the interquartile range). The variables included in the full model are growing degree days (GDD3), calcareousness
545 (CALC), potential solar radiation (RAD) and topographic wetness index (TWI). See table 1 for a full description of each
546 variable. Outliers are excluded for clarity

547

548 **Table S2:** Summary statistics for refugia located by the base (climate-only) and full (climate-plus-landscape) models
549 under Representative Concentration Pathway (RCP) 4.5 and the full model for RCP 8.5 (the base-model for RCP 8.5
550 found no refugia). The full set of variables are growing degree days (GDD3), calcareousness, potential solar radiation
551 (RAD) and topographic wetness index (TWI). See table 1 for a full description of each variable and for comparison with
552 contemporary climatic conditions

553

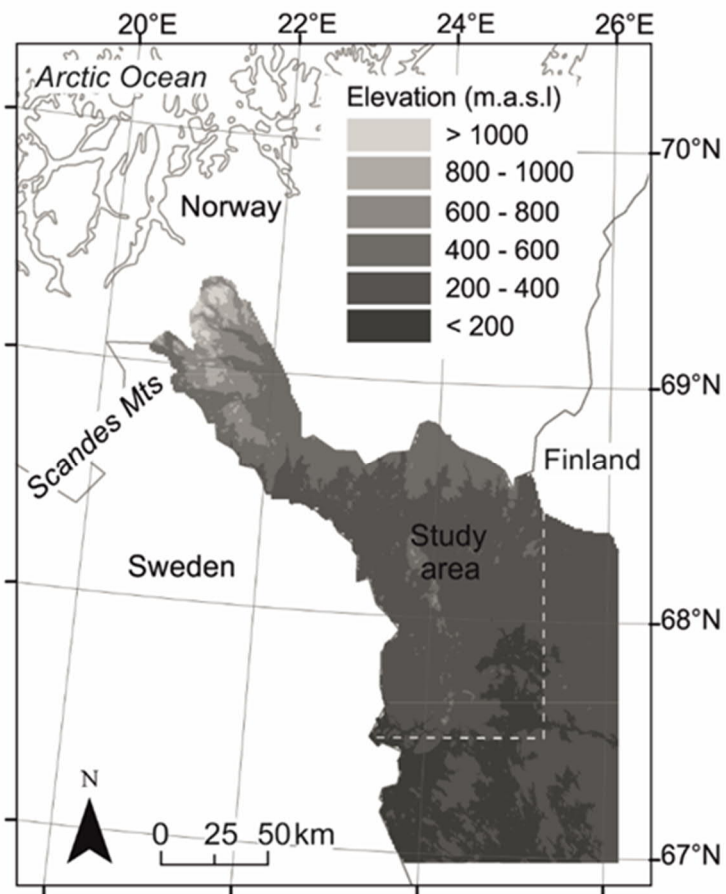
554 **Figure S4.** Spatial characteristics of the predictor variables: growing degree days (GDD3; °C) for the contemporary
555 climate 1981–2010 (a), and GDD3 for the two Representative Concentration Pathway (RCP) scenarios used: RCP 4.5 (b)
556 and RCP 8.5 (c); calcareousness (d; %); potential solar radiation (e; MJ/cm²/a); and topographic wetness index (TWI) (f).
557 See table 1 for a further description of the predictors

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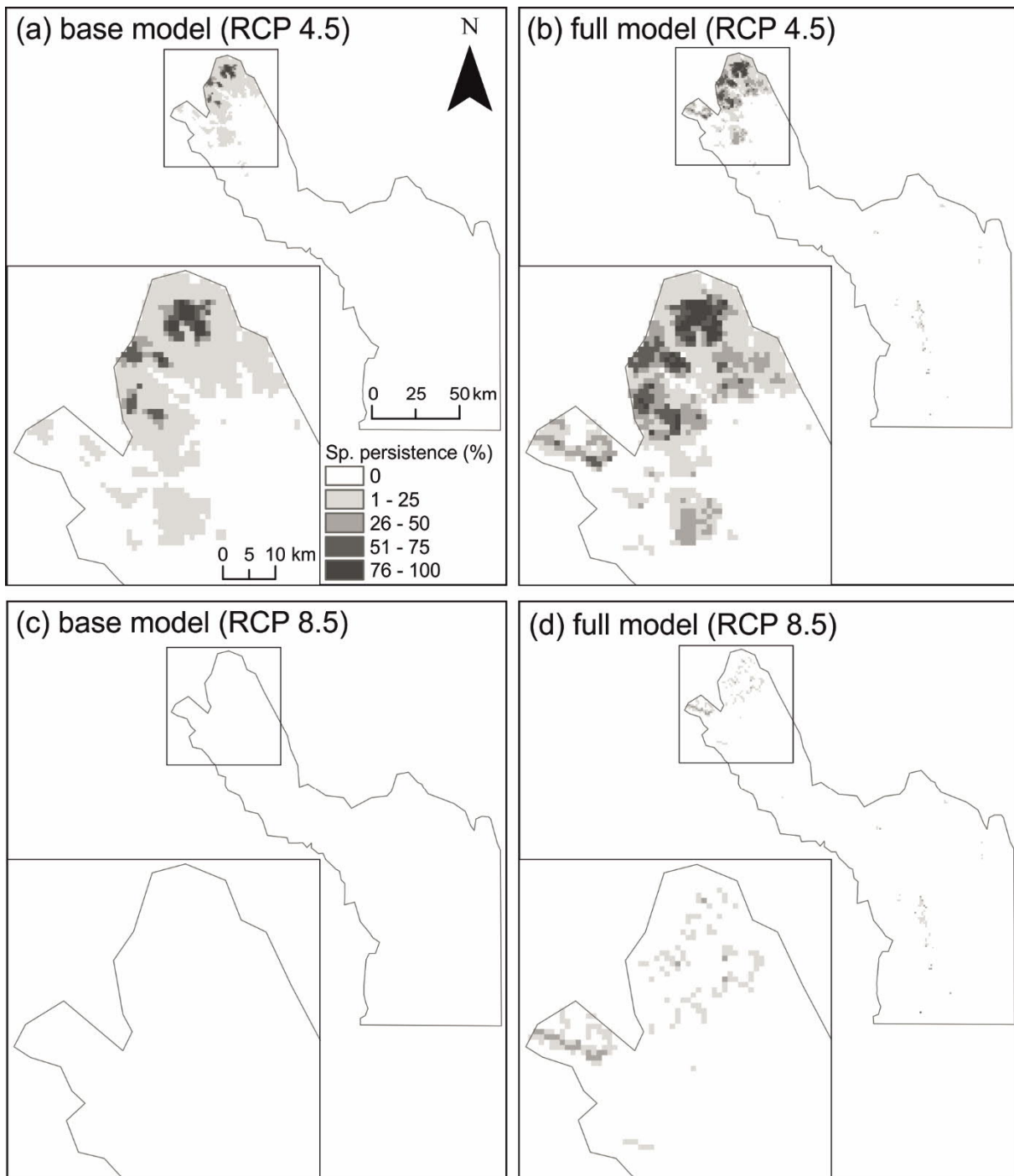
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Figure 1.

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Figure 2.