Consistent trait-environment relationships within and across tundra plant communities

3 Introductory paragraph

4 A fundamental assumption in trait-based ecology is that relationships between traits and 5 environmental conditions are globally consistent. We use field-quantified microclimate and soil 6 data to explore if trait-environment relationships are generalisable across plant communities and 7 spatial scales. We collected data from 6720 plots and 217 species across four distinct tundra 8 regions from both hemispheres. We combine this data with over 76000 database trait records to 9 relate local plant community trait composition to broad gradients of key environmental drivers: 10 soil moisture, soil temperature, soil pH, and potential solar radiation. Results revealed strong, 11 consistent trait-environment relationships across Arctic and Antarctic regions. This indicates that 12 the detected relationships are transferable between tundra plant communities also when fine-13 scale environmental heterogeneity is accounted for, and that variation in local conditions heavily 14 influences both structural and leaf economic traits. Our results strengthen the biological and 15 mechanistic basis for climate change impact predictions of vulnerable high-latitude ecosystems.

16

17 Introduction

A fundamental assumption in trait-based ecology is that trait characteristics of communities
show consistent relationships with environmental gradients ^{1,2,3}. To test this assumption, we ask: *"Are trait-environment relationships consistent within and across tundra plant communities?*"
This important question has rightly received much attention in recent studies ⁴, yet this is the first
test based on a harmonised study design and extensive field-quantified data considering the fine-

scale nature of environmental variation in the tundra ^{5,6}. Plant communities exist on local
gradients of temperature, moisture, and soil chemistry that may correspond in length to the broad
gradients among regions, and therefore fine-scale environmental drivers should be carefully
considered when studying plant-environment relationships. ^{2,7,8}. Moreover, if these relationships
hold along local gradients, they can provide even better insights into urgent questions about the
effects of climate change and help develop a more mechanistic understanding and realistic
predictive ecology across spatio-temporal scales ^{9,10,11}.

30

In the past decades, plant functional trait compositions have significantly changed ⁴, as tundra 31 ecosystems have experienced rapid climate change ^{12,13,14}. Plant traits can be rough proxies for 32 33 ecosystem functioning and respond to the biogeochemical and biophysical properties of ecosystems ^{15,16,17,18}. Above-ground traits vary primarily on two axes ^{17,18,7,19}. One axis 34 35 differentiates plant species and communities according to size-structural traits affecting, for instance snow trapping ²⁰, shading ²¹, albedo ²², and carbon cycling ²³. The other axis describes 36 37 variation in leaf economics and resource-use strategy, which influences photosynthetic efficiency, biogeochemical cycles, and forage quality ^{24,25}. In tundra, size traits, such as plant 38 height, are positively correlated with warming⁴. This is important, because plants are closely 39 40 connected to the carbon cycle and half of the global below-ground carbon stock is located in tundra soils ^{10,26}. Recent shifts in tundra vegetation are linked back to climate change, therefore 41 42 the investigation of trait-environment relationships in the tundra is relevant beyond the scope of the high-latitudes or theoretical ecology 4,27,28 . 43

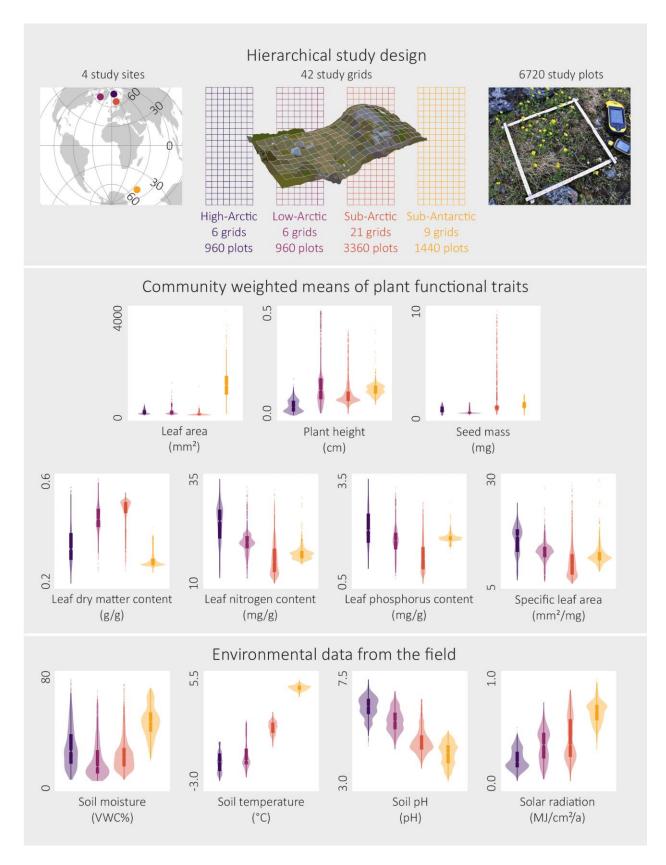
45 As temperatures, precipitation, and environmental conditions overall are changing in both Arctic and Antarctic tundra ^{29,30,31,32,33}, an open question is, how will these changes influence ecosystem 46 functioning? In tundra, geographic distributions of species are largely determined by variation in 47 snow cover ^{34,20,35}, resource availability ^{36,37,38}, and the length of the growing season ^{39–41}. These 48 49 abiotic conditions can vary dramatically at fine spatial scales ^{5,8}, driving variation in diversity and composition of plant communities over short distances 42,43,44. Thus, we test the strength of 50 51 trait-environment relationships with predictors at two spatial scales: 1) fine-scale field measurements representing microclimate and local soil chemistry (1 m^2) , and 2) coarse-scale 52 53 climate and soil data representing macroclimate and coarse-scale soil chemistry (1 km^2) . We 54 hypothesise that the former outperforms the latter, as coarse-scale data depicts local heterogeneity poorly ^{6,45}, and thus, the fine-scale field-quantified environmental factors are 55 56 expected to provide stronger evidence for the existence of universal trait-environment 57 relationships.

58

59 <u>Results</u>

60 We collected detailed data on vascular plant community compositions and local abiotic 61 conditions across four geographically and climatically distinct tundra sites in the high-Arctic 62 Svalbard, low-Arctic western Greenland, sub-Arctic northern Fennoscandia, and sub-Antarctic 63 Marion Island (for study design and data details, see Methods and Figure 1). In each of the 6720 64 vegetation plots (1 m^2) within 42 sampling grids (8 m x 20 m, 160 plots each), we analyse the 65 community weighted means (CWM) of key plant functional traits related to vegetation structure 66 (namely, leaf area, plant height, and seed mass) and the leaf economic spectrum (leaf dry matter 67 content, leaf nitrogen content, leaf phosphorus content, and specific leaf area). We collected *in*

- 68 situ species composition data across wide gradients of microclimatic conditions and soil
- 69 chemistry, and we combine this with over 76000 trait records from global databases provided by
- 70 the Tundra Trait Team, TRY Plant Trait Database, and the Botanical Information and Ecological
- 71 Network ^{46,47,48}.



73 Figure 1. Data and study design. We collected data from four tundra sites. Each of the sites had 74 multiple sampling grids, which were situated in topographically complex landscapes to maximise 75 environmental variation within a restricted spatial extent (8 m x 20 m). Each grid consists of 160 76 plots (1 m x 1 m). From each plot, we collected in situ data on plant species composition and 77 field-quantified key environmental drivers, and extracted species trait records from databases 78 from which we calculated the community weighted means of key plant functional traits. Data 79 (non-transformed) on the variables are presented as violin plots overlaid with box plots. In the 80 box plots, the notches and hinges represent the 25th, 50th, and 75th percentiles, with whiskers 81 representing 95% confidence intervals, and with outliers shown as points. In the violin plot, the 82 thickness of the violin polygon corresponds to the local density of the observations.

83

We collected data on field-quantified environmental drivers, namely, soil moisture, annual mean soil temperature, soil pH, and potential solar radiation. This revealed pronounced fine-scale variation as well as larger environmental gradients within and across the four study sites. For example, soil pH ranged from 4.7 to 7.4 within the high-Arctic site located in Svalbard and its overall range across all the sites was from 3.3 to 7.4 (Figure 1). The ranges of the environmental variables generally overlapped among the sites, except for soil temperature (Figure 1).

We used the environmental variables as predictors in hierarchical generalized additive models (HGAM), a powerful tool for modelling variability among sites ⁴⁹. HGAM allows the use of flexible response shapes, and thus, enables inferring if the trait composition at different sites follows a "global" trait-environment relationship; that is a relationship transferable within the four study sites ⁴⁹. We use HGAMs to study whether the functional relationships between plant

traits and the environmental drivers are consistent across the four study sites, as we are interested
to determine if trait-environment relationships are "global" (generalisable among the sites) rather
than "local" (restricted by unique responses of local species pools).

99

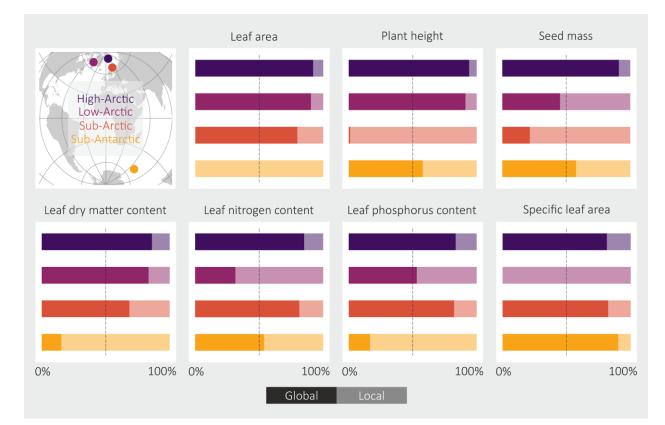
100 First, we calculated the amount of variation, which we measured as range and standard deviation, 101 in the CWM traits and environmental variables within the 42 study grids and compared these to 102 the total variation in the entire dataset (Appendix 1). We found that soil moisture shows 103 especially great within-grid variability: on average a grid has approximately 50% of the variation 104 of the entire dataset. Of the four environmental variables, soil temperature displays the least 105 within-grid variability. Regarding the CWM traits, plant height and specific leaf area varied most 106 over short distances, while leaf area and leaf dry matter content had the least pronounced within-107 grid variability of the seven CWM traits.

108

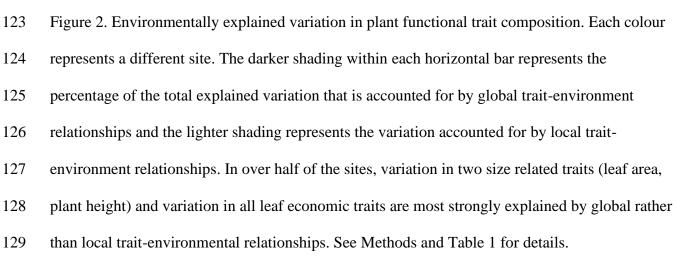
109 We found consistent trait-environment patterns across the four sites (Figure 2). In 20 out of 28 110 trait-site comparisons, environmentally explained trait composition was more strongly 111 determined by global trait-environment relationships than by local deviations from the global 112 pattern. The global trait-environment relationship is determined with the data from all four sites, 113 whereas the local deviation is determined only by site-specific data. In other words, in models of 114 trait composition, including smoothers describing the global trait-environment relationships increased model r^2 more than further adding smoothers accounting for local deviations from the 115 116 global trend (Table 1). The trait-environment relationships are thus not dependent on 117 geographical location, which means that community-level plant traits respond to environmental 118 variation consistently across the tundra sites, forming a general and transferable pattern. We also

119 compared our fine-scale *in situ* environmental data with coarse-scale climate and soil data, and

120 we found the first to outperform the latter for all seven plant functional traits (see Methods and



121 Appendix 2 for details).



- 130 Table 1. The r^2 values for the models divided between the random effect, the global trait-
- 131 environment relationship, and the local trait-environment relationship. The higher the value, the

Plant trait	Site	Random effect	Global relationship Local relations	
	High-Arctic	0.22	0.35	0.03
Leaf area	Low-Arctic	0.11	0.37	0.04
	Sub-Arctic	0.27	0.21	0.05
	Sub-Antarctic	0.30	-0.01	0.06
	High-Arctic	0.19	0.38	0.02
Plant height	Low-Arctic	0.02	0.28	0.03
	Sub-Arctic	0.18	0.00	0.08
	Sub-Antarctic	0.32	0.03	0.02
	High-Arctic	0.12	0.35	0.03
Seed mass	Low-Arctic	0.05	0.14	0.17
Seed mass	Sub-Arctic	0.22	0.03	0.10
	Sub-Antarctic	0.17	0.05	0.04
	High-Arctic	0.42	0.18	0.03
Loof dry matter content	Low-Arctic	0.20	0.24	0.05
Leaf dry matter content	Sub-Arctic	0.19	0.20	0.09
	Sub-Antarctic	0.35	0.03	0.18
	High-Arctic	0.21	0.24	0.04
Loof nitrogon contont	Low-Arctic	0.15	0.06	0.13
Leaf nitrogen content	Sub-Arctic	0.24	0.21	0.05
	Sub-Antarctic	0.00	0.12	0.10
Leaf phosphorus content	High-Arctic	0.34	0.24	0.05
	Low-Arctic	0.19	0.16	0.14
	Sub-Arctic	0.25	0.19	0.04
	Sub-Antarctic	0.02	0.04	0.21
	High-Arctic	0.45	0.14	0.03
Specific loof area	Low-Arctic	0.15	-0.03	0.10
Specific leaf area	Sub-Arctic	0.30	0.23	0.05
	Sub-Antarctic	0.01	0.10	0.01

132 greater proportion explained by the factor.

133 134

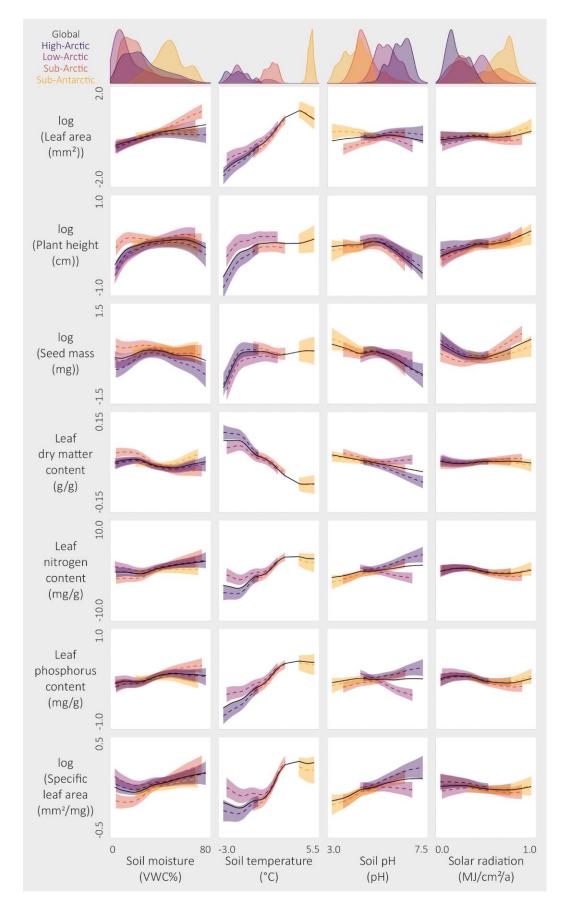
135 In addition, we carried out a principal component analysis (PCA) to investigate the key

136 dimensions in both the environmental and trait space, as well as the correlation between the two

137 spaces (Appendix 3, Appendix 4). All variables were scaled to unit variance. The primary axis in

138 the trait space (55.22% of the total variance) was related to the leaf economic spectrum (leaf dry

- 139 matter content, leaf nitrogen content, leaf phosphorus content, and specific leaf area) and
- 140 correlated (0.40) with the secondary axis of the environmental space (20.97%) related to soil
- 141 moisture. The secondary axis in the trait space (22.46%) was related to structural traits (leaf area,
- 142 plant height, and seed mass) and correlated (0.67) with the first axis of the environmental space
- 143 (58.87%) related to soil temperature, soil pH, and radiation.



146 Figure 3. Plant functional trait-environment relationships. The black line represents the spline for 147 the global trait-environment relationship (that is, the trend based on all data from all four sites). 148 The coloured lines represent the sum of the global spline and the spline depicting the local 149 deviation from the global trait-environment relationships. The shaded areas represent two 150 standard deviations for each spline, taking into account the uncertainty in both the global and the 151 local smoothers. The analysis was based on a hierarchical generalized additive model, using 152 global and group-level (that is, one for each of the four sites) smoothers (for details, see 153 Methods). Density plots in the top row represent the distribution of the environmental variables 154 at each site.

155

156 The responses of plant functional traits to environmental drivers were chiefly globally consistent 157 (Figure 3, Figure 2). The traits responded strongly to soil temperature, with particularly large 158 changes at the 0°C mean annual temperature threshold. For example, at higher soil temperatures, 159 plants on average grow taller and have larger leaves with higher nitrogen and phosphorus 160 contents. In addition, we assessed the relative importance of the environmental drivers 161 explaining community composition (Appendix 5). The results concurred with the response 162 curves (Figure 3), showing chiefly that trait composition responds most strongly to soil 163 temperature, both within and across sites.

164

165 Discussion

166 **Consistent trait-environment relationships**

167 We found consistent relationships between plant functional traits and local environmental

168 conditions across tundra plant communities. Our findings show strong, field-quantified fine-scale

evidence for one of the core claims in trait-based ecology: trait-environment relationships are
generalisable across geographical locations and taxonomic composition. In 20 out of 28
comparisons, the trait-environment relationship was most strongly explained by global traitenvironment relationships (Figure 2, Figure 3). Importantly, considering the fine-scale
environmental gradients and communities in the analyses did not generate random noise but
made the relationships even stronger compared to the coarse-scale investigations (Appendix 2).
These patterns hold across unique species pools and other site-specific characteristics.

176

177 The trait-environment relationships differ in magnitude and transferability (Figure 2, Figure 3, 178 Table 1). All traits were strongly and consistently related to soil temperature. The relationships to 179 soil moisture and potential solar radiation were consistent but weaker. In some sites, the 180 relationship between traits and soil pH was the opposite compared to other sites. However, even 181 if some sites showed minor local deviations from the global trait-environment relationship, they 182 manifested in only one environmental variable - site -combination per trait, and do not change 183 the general pattern: trait-environment relationships are generalisable within and across the four 184 tundra plant communities and the seven traits.

185

The magnitude of local variation in trait composition and environmental conditions is itself an important determinant of the transferability of trait-environment relationships, as shorter local gradients lead to higher uncertainty in the direction and magnitude of the relationships. In our results, local trait-environment relationships were reversed when local gradients were short compared to the full range of environmental variation, for example soil pH in the low-Arctic site and soil temperature in the sub-Antarctic site (Figure 3). Thus, our results emphasise the

importance of covering as broad local gradients as possible when investigating fine-scale
vegetation patterns ⁵⁰.

194

195 Our results are based on a hierarchical statistical analysis of strictly quantitative and 196 harmoniously collected data across four tundra sites located on both hemispheres. Our in situ 197 investigations concur with the results reported in previous literature, as we found support for 198 trait-environment relationships based on gridded climate datasets suggesting strong biome-wide 199 links between temperature and plant height, leaf dry matter content, and specific leaf area ⁴ 200 (Figure 3, Appendix 5). Similar results to the generalised relationships found in our study have 201 also been reported beyond the tundra for temperature and soil moisture in central Europe ⁵¹. Our 202 results together with existing literature provide robust evidence for globally generalisable traitenvironment relationships beyond a single study ^{1,2,51,4}. 203

204

205 Fine-scale variability and large gradients

206 We found strong fine-scale variation and large gradients of soil moisture at all four sites (Figure 207 1, Appendix 1). In rugged tundra landscapes, topographic variation can create contrasting moisture conditions within a few meters distance ^{8,44,52}. Across the sites, we derived moisture 208 209 data from the top-soil layer (0 - 10 cm). The moisture conditions ranged from extremely dry soils 210 found on small hilltops and ridges to water-logged conditions in depressions (15 - 70 volumetric 211 water content %; Figure 1). Our results indicate that most plant traits are positively correlated 212 with soil moisture (Figure 3). These results provide quantitative evidence to support research that 213 have shown that soil moisture regime influences the strength and direction of trait-temperature relationships in the tundra⁴. Overall, soil moisture is a vital resource for tundra plants⁵³. It 214

distributes nutrients and influences geomorphological disturbance ^{54,55,56}, and in turn, controls the
overall establishment of vegetation and contributes to providing refugia together with other
microclimatic factors in a warming climate ^{57,58,59}.

218

219 We found that temperature was a strong driver of trait variation at a fine spatial scale (Figure 3; 220 Appendix 5), in line with previous studies that have found a positive relationship between plant 221 height and temperature at a coarse spatial scale⁴. We derived the mean annual temperature from 222 miniature loggers (buried at 5 to 10 cm depth). Thus, it is evident that the temperatures also 223 reflect the pivotal winter conditions, to which the plants are exposed, as our study sites chiefly experience long winters, short growing-seasons, and seasonal snow coverage ⁵⁰. These 224 conditions are changing dramatically in the high-latitudes ^{29,30}. This change is significant for both 225 226 plant functional composition and species composition, as they are strongly affected by snow in the tundra ^{60,35,61,4}. Nevertheless, climate change will not result in consistently warmer conditions 227 across the high-latitudes ²⁹, as, for instance, parts of Antarctica are also cooling ⁶². 228

229

230 We found higher mean annual soil temperatures at the sub-Antarctic site located on Marion 231 Island compared to the Arctic sites, where temperatures drop below 0°C. This may explain why 232 the traits did not respond as strongly to soil temperature at the sub-Antarctic site compared to the 233 Arctic sites and why leaf area had a negative response to temperature at the sub-Antarctic site 234 (Figure 3). These results may be due to the strong oceanicity (and, as a result, very buffered thermal regime) of the site compared to the Arctic sites ⁶³. Marion island is also part of a small 235 236 and extremely remote sub-Antarctic island group with especially low vascular plant species richness ⁶⁴. Thus, the species pool at the sub-Antarctic site may be strongly filtered by 237

environmental factors other than the prevailing abiotic conditions, for instance long-distance
dispersal, and thus, different responses to temperature compared to the Arctic sites are not
surprising.

241

242 We observed that higher soil pH corresponded with decreased average seed size and faster leaf 243 economic traits (higher specific leaf area, leaf nitrogen content, and leaf phosphorus content, and 244 lower leaf dry matter content). Higher soil pH increases nutrient mineralisation rates and is related to local soil nutrient availability ^{65,66}. Consequently, our results suggest that higher soil 245 246 nutrient availability leads to plant communities that invest in fast acquisition of resources, and 247 produce smaller seeds. Both observations agree with theory. Resource conservation is a losing strategy in conditions of high resource availability ⁶⁷. Furthermore, the benefit of equipping 248 249 seeds with large stores of nutrients and energy decreases when soil resource availability is high but productivity is not high enough to trigger exclusion by shading ⁶⁸, as is probably the case in 250 251 these tundra landscapes. However, the leaf economic traits in the relatively alkaline soils in the 252 low-Arctic site in Greenland did not respond to soil pH in concordance with the other tundra 253 sites (Figure 1, Figure 3). This mismatch is probably not due to trait responses to nutrient 254 availability being idiosyncratic, but the fact that pH is an incomplete proxy for nutrient 255 availability, whose usefulness might depend on soil acidity ⁶⁹ or soil-specific factors that affect 256 pH independently of nutrient mineralisation rates.

257

Potential solar radiation is relatively important for plant community composition and species
 richness in the tundra ^{50,53} However, we found that trait compositions were not strongly related to
 solar radiation, nonetheless the size-structural traits, plant height and leaf area, had a positive

261 relationship with solar radiation after accounting for the other environmental factors (Figure 3). 262 Thus, we expect communities composed of larger plants under conditions of more potential 263 incoming solar energy. Other studies have found actual incoming radiation to affect leaf economic traits as well ^{70,71}, but these studies were mainly conducted in forests where the chief 264 265 control of exposure to sunlight is the density of the tree canopy. Our study suggests that the leaf-266 economic trait composition of tundra plant communities is less directly affected by varying solar 267 conditions. This may be perhaps because locally measured temperatures already partly reflect 268 incoming energy, and because radiative conditions in treeless biomes are more homogeneous 269 compared to environmental factors that vary at finer scales, such as soil temperature or soil 270 moisture ^{72,44,73}.

271

272 Our fine-scale field investigations revealed large local gradients in both traits and key 273 environmental drivers, namely microclimatic conditions and soil chemistry, in four distinct 274 tundra systems (Figure 1, Appendix 1; for biome-wide traits, see ⁴). It is notable that in tundra 275 environments CWM traits may vary on a 20 m distance (that is the extent of an individual study 276 grid; see Figure 1 for details) nearly as much as they vary across four contrasting Arctic and 277 Antarctic sites (Appendix 1). Environmental conditions also varied considerably over short 278 distances. However, it should be noted that due to evident limitations of the trait data, we cannot 279 consider the effects of intraspecific trait variation (ITV) along the microclimatic gradients, and 280 thus, we cannot explicitly evaluate how this may impact our results. Nevertheless, biome-wide 281 explorations have demonstrated that ITV varies largely in the same direction as the trait variation caused by species turnover along the environmental gradients⁴. Therefore, it is reasonable to 282

assume that accounting for the ITV in our analysis should at least not weaken the trait-environment relationships found here.

285

286 Microclimate and macroclimate

287 We found that fine-scale *in situ* data outperformed coarse-scale climate and soil data in 288 modelling the trait-environment relationships (Appendix 2). This suggests that fine-scale 289 environmental drivers, such as microclimate, are important for understanding and predicting the 290 current and future microhabitat conditions affecting community composition and functioning ^{72,74}. However, the interactions between vegetation, microclimate, and macroclimate are complex 291 292 ⁷⁵. This is because microclimate is a result of various horizontal (such as vegetation structure, 293 and snow and soil characteristics) and vertical processes (e.g. effects of local topography on incoming radiation and air flow)⁴⁵. One consequence of these processes is that microclimate 294 may buffer against unfavourable changes in the macroclimate ⁵⁹ via for instance, soil moisture, 295 which reduces the variability in local temperatures ^{76,77}. This may potentially be one mechanism 296 297 through which soil moisture can influence the strength and direction of plant trait-temperature 298 relationships⁴. Equally, vegetation is affected by both microclimate and macroclimate, but it also affects both, especially microclimate by, for instance, shading and transpiration ^{21,77}. 299 300 Consequently, the local manifestation of climate change and the response of plants are challenging to predict ^{76,6}. 301

302

We measured environmental drivers at a biologically-meaningful scale, which captures the local heterogeneity in the microhabitats that plants experience ⁴⁴. However, this variation created by topography may be undetected (or averaged over) when using coarse-scale data ⁷⁶. Coarse-scale 306 studies investigating variation in plant traits at the community-level typically only explain a relatively small proportion of the variation in functional composition ^{7,4}. This is most probably 307 308 due to low-resolution environmental data, which ignore the fine-scale nature of the environmental drivers ^{5,6,76,72}. For example, precipitation is typically weakly related to traits as it 309 poorly captures the actual plant-available water ^{7,78,79}. Even though microclimate and 310 311 macroclimate are interrelated, local heterogeneity in environmental conditions can be more 312 important for plant distributions and functional composition than coarse-scale macroclimatic factors ^{6,60,73}. Therefore, as more trait data is made available globally through trait databases, 313 314 more field-quantified microclimate data are urgently needed to document trait-environment relationships, and to determine their generality, across other biomes ^{80,45}. New frameworks and 315 316 techniques for recording and producing estimates of soil moisture and temperature data are available ^{81,82,83,84}, as well as new methods for modelling past, current, and future conditions 317 ^{85,74,86}. Therefore, when exploring fine-scale trait ecology, we encourage considering the use of 318 319 microclimate predictors at an ecologically relevant scale.

320

321 The future of the tundra and beyond

Experimental and observational studies have shown that tundra plant communities and functional composition are responding to the changes in climate (see ^{87,88}). For example, biome-wide longterm monitoring has shown an increase in plant height in reaction to warming temperatures in the tundra over a 30-year period, but no concurrent rapid changes in community-level leaf economic traits ⁴. Therefore, together with previous literature, our results suggest that it is very likely that as temperatures rise at high-latitudes plants will grow taller. It is also possible (especially over longer periods) that warming will lead to an increase in leaf size ⁴, and if sufficient moisture is
available, to higher leaf nutrient levels.

330

331 Temperature, precipitation, snow, permafrost, and the overall hydrological conditions in tundra are changing 89,90 , and consequently, the availability of soil moisture will also likely change 30 . In 332 333 the Arctic, snowfall in general is expected to decrease, while rainfall is increasing ³¹, which is 334 partly explained by regional warming ⁹¹. In contrast, nonetheless, in parts of the Arctic, a net water deficit has, for instance, caused ponds and lakes to dry over the past decades ^{92,93,94}. As a 335 336 result, many tundra ecosystems have shown strong negative responses to regional drying, such as 337 large changes in moss vitality and community composition and declines in bird species richness 338 ^{12,95}. We expect that both temporal and spatial variation in plant-available water will significantly 339 influence vascular plant communities as well, and water will be an even more important resource and disturbance in the warmer future of the tundra ecosystems ^{53,56}. 340

341

342 Our results highlight clear correlations between microclimatic conditions and key plant traits. In 343 turn, this may have reciprocal effects on, for instance, local moisture conditions, as plants transpire water ⁹⁶, intercept precipitation ⁹⁷, and increase the hydraulic redistribution in soils ⁹⁸. 344 345 The expected changes in tundra ecosystems' functions and processes may thus influence microclimatic conditions ^{21,96,99}, and in turn, also have dramatic impacts on nutrient and carbon 346 cycling ^{100,101}. For instance, shrub expansion is expected to feedback onto climate change 347 through changes in ecosystem functions and processes ^{10,23}. However, there is currently no 348 349 consensus on, for instance, how the expansion of woody plants may affect the tundra carbon

cycle ^{23,102,103}. Nevertheless, there is great potential for the use of plant functional traits to
examine changes in the above- and below-ground ecosystem functioning of the tundra.

352

353 Conclusions

To conclude, we find strong, consistent trait-environment relationships across four sites located in the high-Arctic, low-Arctic, sub-Arctic, and sub-Antarctic tundra. We used a harmonised study design consisting of field-quantified data, which often is lacking from coarse-scale studies. Our results show that these trait-environment patterns are universal across four distinct tundra ecosystems, as local variation within the sites was overridden by strong, global trait-environment relationships. This knowledge is significant for improving the biological basis for climate change impact predictions for vulnerable high-latitude ecosystems.

361

362 Material and methods

363 Study design

All plant species data and abiotic data have been collected following a peer-reviewed, harmonised field protocol ^{44,53}. We surveyed 42 study grids: six grids in the high-Arctic, six in the low-Arctic, 21 in the sub-Arctic, and nine in the sub-Antarctic. Each grid contained 160 study plots of 1 m² and covered a range of environmental conditions (see for instance ⁷⁷). In total, we collected the plant species composition and abiotic data from 6720 plots (see Figure 1 for details on the data).

370

371 We chose the locations of the sites based on their topographic and vegetation gradients (Figure

372 1). We situated the study grids within each site to maximise variation in mesotopography 5,8 , as

well as vegetation cover and composition. Despite their floristic dissimilarities, these regions
have several shared characteristics, with, specifically, the sub-Antarctic and sub-Arctic tundra
exhibiting a similar range of vegetation types ⁶³. All sampled landscapes are dominated by
alternation of minor topographic terrain features, such as hilltops, ridges, and small depressions.
In addition, there are several substrate types ranging from rock outcrops, boulders, glacial till,
and fluvial deposits to peat deposits.

379

380 Study sites

381 High-Arctic site

382 The high-Arctic study site is located in Svalbard, on the slopes of Adventdalen and Endalen

valleys (78.20 N, 15.73 E). We collected the abiotic and biotic data in the 2018 growing-season.

384 On average, the annual temperature is -5.9 °C and precipitation 196 mm (1971–2000), as

measured at the Svalbard Airport observation site (78.25 N, 15.50 E; 28 m a.s.l.), which is

386 located 7.7 km from the study site ¹⁰⁴. The site is dominated by *Dryas octopetala*, *Salix polaris*,

387 and Cassiope tetragona, and to a lesser extent by Bistorta vivipara, Festuca rubra, and Poa

388 *pratensis.* The elevation of the study grids ranged from 30 to 110 m a.s.l..

389

390 Low-Arctic site

391 The low-Arctic study site is located in western Greenland, on the highland of Ammalortup

392 Nunaa (66.95 N, -50.72 W). We collected the abiotic and biotic data in the 2018 growing-season.

393 On average, the mean annual temperature is -4.9 °C and annual precipitation 252 mm (1977-

394 2013) as measured at the Kangerlussuaq Airport (67.02 N, -50.70 W; 50 m a.s.l.), which is

395 located 7.0 km from the study site ¹⁰⁵. The site was dominated by *Vaccinium uliginosum*, *Betula*

396	nana, and Salix glauca, and to a lesser extent by Cassiope tetragona, Salix herbacaea, and
397	Rhododendron tomentosum. The elevation of the study grids ranged from 520 to 560 m a.s.l
398	

399 Sub-Arctic site

- 400 The sub-Arctic study site is located in northwestern Fennoscandia, on Mount Saana (69.05 N,
- 401 20.81 E). We collected the biotic data over three consecutive growing-seasons (2011 2013),
- 402 and abiotic data in the 2013 growing-season. On average, the mean annual temperature is -3.1 °C
- 403 and annual precipitation 518 mm (1991–2018), temperature measured at the nearby Saana
- 404 meteorological station (69.04 N, 20.85 E; 1002 m a.s.l.) and precipitation at Kyläkeskus
- 405 meteorological station (69.04 N, 20.80 E; 480 m a.s.l.), which are located ca. 1.5 km and 1.0 km
- 406 from the study site ^{106,107}. The site was dominated by *Empetrum hermaphroditum*, *Betula nana*,
- 407 and Juniperus communis, and to a lesser extent by Vaccinium vitis-idaea, Vaccinium uliginosum,
- 408 and Vaccinium myrtillus. The elevation of the study grids ranged from 595 to 810 m a.s.l.. All
- 409 the grids were situated above the treeline (comprised of *Betula pubescens* ssp. *czerepanovii*).

410

411 Sub-Antarctic site

The sub-Antarctic study site is located on Marion Island in the southern Indian Ocean (-46.90 S, 37.73 E). The data were collected over one year, from autumn 2016 to autumn 2017. The mean annual maximum temperature is 8.7 °C, with a mean annual minimum temperature of 3.2 °C, and mean annual precipitation of 1800 mm (2008 - 2018, measured at the nearest weather station, approximately 1 km away). The island has a hyper-oceanic climate, characterised by low temperatures, low variations in temperature and high humidity ⁶⁴. Gale force winds blow on more than 100 days of the year and most days experience precipitation and near-complete cloud 419 cover ⁶⁴. The main vegetation types at the site are fernbrake (dominated by the fern *Blechnum*420 *penna-marina*), mire (dominated by the grass *Agrostis magellanica*) and fellfield (dominated by
421 the cushion plant *Azorella selago*; for details see ¹⁰⁸). The elevation of the study grids ranged
422 from 40 to 104 m a.s.l..

423

424 Vegetation data

425 We identified all vascular plant species and estimated their cover percentage in the 6720 plots 426 (see full species list in Appendix 6). We extracted trait observations for seven plant functional 427 traits (namely, plant height, specific leaf area, seed mass, leaf dry mass content, leaf area, leaf 428 nitrogen content, and leaf phosphorus content) for each species from three databases: the Tundra Trait Team database (TTT ⁴⁶), TRY Plant Trait Database (TRY ⁴⁸), the Botanical Information 429 and Ecological Network (BIEN⁴⁷) and from published articles and theses' (see Appendix 7 for a 430 431 full citation list of the trait data). We searched the databases for the full species list (including 432 their synonyms), which we recorded at our study sites. Additionally, for genus-level trait values, 433 we extracted trait observations from TRY for all species occurring in TTT database and in 434 Fennoscandian countries according to the occurrence records of the Global Biodiversity 435 Information Facility (GBIF; https://www.gbif.org/). From BIEN, we searched data by using all 436 genera found in our vegetation plot dataset. The nomenclature of all datasets was standardised to 437 match to the GBIF backbone nomenclature.

438

TRY trait observations correspond to TRY trait ID numbers 3106 (plant height), 3115, 3116, and
3117 (specific leaf area), 26 (seed mass), 47 (leaf dry matter content), 3108, 3109, 3110, 3111,

3112, 3113, and 3114 (leaf area; for species with compound leaves only 3108, 3110, 3112, and
3114), 14 (leaf nitrogen content), and 15 (leaf phosphorus content).

443

We cleaned the combined trait data chiefly following the data cleaning procedures *sensu*⁴. For each observation, we determined its error risk by calculating how many standard deviations (SD) it differs from the mean of the given species and trait (the focal observation excluded in the SD and mean calculations). If there were less than four trait observations we included all data, if less than 10 observations we included only observations with error risk less than 2.25, and otherwise we used an error risk threshold of three.

450

451 In addition, we plotted the histograms of trait observations for each species and trait and based 452 on expert knowledge we manually excluded trait values that were considered impossible in the 453 context of tundra vegetation, for instance 10 m for the height of Juniperus communis or 454 otherwise suspicious values. If a species missed data for a trait, we used genus-level 455 observations. Here, we selected only georeferenced observations within the tundra climatic zone (class "ET" in ¹⁰⁹) and then averaged the trait values over the species within the genus. After 456 457 filtering, we had 76475 trait observations at the species level for the species recorded in the study 458 plots and an additional 38322 observations (partially overlapping with the former), which we 459 used to calculate the genus-level traits, if no species-level data were available.

460

461 We used hierarchical sampling and bootstrapping to construct community weighted mean

462 (CWM) values for the vegetation plots to account for the varying relevance of the trait

463 observation for tundra vegetation and the intraspecific variation present in the trait observation

464 data (we used a slightly modified version of the code available at

https://github.com/richardjtelford/traitstrap). For each trait observation, we checked whether it
had location information, and for georeferenced observations, we extracted information about its
climate using a fine-scale climate classification ¹⁰⁹.

468

469 First, we used five nested hierarchies to classify the relevance of the trait observations: three 470 nested Köppen-Geiger climate classifications (I-III), the status of georeferencing (IV), and the 471 global level, in which all trait records were included (V). Then each trait observation got a 472 weight based on the abundance of the species in a plot, which is the finest hierarchy level at 473 which the trait observation matches to the plot data. This means that for example a georeferenced 474 trait observation recorded within the tundra climate class (matching all hierarchy levels with our 475 plot data) got five times a higher weight (because of the I-V hierarchy levels) compared to a non-476 georeferenced global-level observation. Based on these weights, we took a random sample of 477 100 trait observations and calculated the CWM values for each plot. We repeated this sampling 478 100 times for each plot to see how much the intraspecific variation in the trait data affects the 479 CWMs. We selected CWMs to the statistical analyses only if trait data (species or genus level) 480 were available for the species that comprise at least 90% of the total cover in the plot.

481

Depending on the trait, species-level trait data covered on average 96.9% (seed mass) to 99.5%
(plant height) of the recorded species weighted by their cover in the study plots. When genuslevel trait data was included the corresponding numbers were 99.1% and 99.9%. The average
number of trait observations per species weighted by their abundance in the plots varied between
32.9 (seed mass) and 667.0 (plant height) depending on trait. See Appendix 8 for a

487 comprehensive summary and basic statistics of the coverage of the trait data and CWM
488 bootstrapping estimates by study site and by functional trait.

489

In the analyses, we use CWM and log-transformed the following traits: plant height, specific leaf area, seed mass, and leaf area. We had 61 vascular plant species from the high-Arctic, 75 from the low-Arctic, 134 from the sub-Arctic, and 18 from the sub-Antarctic (see full species list in Appendix 6). In total we had 217 species, of which 88 species were found in more than one of the sites. If traits were available, ferns were included in the analyses, except for the seed mass analysis.

496

497 Environmental data

498 Soil moisture

499 In tundra, plants distribute a large part of their biomass below ground surface, as their roots are relatively shallow ^{110,111}. The rooting depth of plants is limited due to permafrost and a rather 500 shallow A-horizon ¹¹², consequently, plant-available water is found in the top-soil layer ^{53,55}. We 501 502 used a hand-held time-domain reflectometry sensor to measure soil moisture (as volumetric 503 water content (VWC%)) up to a depth of 10 cm in the low-Arctic site and 7.5 cm in the rest of 504 the sites (FieldScout TDR 300; Spectrum Technologies, Plainfield, IL, USA). Soil moisture was 505 measured once in the high-Arctic and low-Arctic sites (August 8th and July 9th 2018), on three 506 occasions in the sub-Arctic site (June 12th to 13th; July 23rd to 24th; August 9th 2013), and on 507 five occasions in the sub-Antarctic site (June 22nd, July 27th, October 3rd 2016; January 26th 508 and April 15th 2017). On each sampling occasion, three measurements were taken from each 509 plot, accounting for possible within-plot moisture variation. Consequently, the mean of the three 510 points was used for calculating the soil moisture level of each plot. In sites where we measured 511 soil moisture on several occasions, we took the mean of the measurements to represent the 512 overall soil moisture level of a given plot ^{44,52}. To ensure comparability of measurements, each 513 set of measurements was taken on a day where there had been no precipitation for at least the 514 preceding 24 hours ⁸².

515

516 Soil temperature

517 We measured soil temperature using miniature temperature loggers (Thermochron iButton 518 DS1921G and DS1922L; temperature range between -40 and 85°C, resolution of 0.5°C, and 519 accuracy of 0.5° C). We installed the loggers 5 to 10 cm below the ground surface. The loggers 520 collected data for one year with 2-4 hour intervals (except at the sub-Antarctic site where the 521 year fell short by two weeks). High-quality data were obtained from 69 loggers from the high-522 Arctic site in 2018-2019, 72 from the low-Arctic in 2018-2019, 322 from the sub-Arctic in 2013-523 2014, and 52 from the sub-Antarctic in 2016-2017. The study grids had a maximum of 18 524 loggers per grid and a minimum of three. We calculated mean annual soil temperature for each 525 logger plot and estimated values for the remaining plots using bilinear interpolation. We forced 526 the values to stay between the minimum and maximum of the true measured mean annual soil 527 temperatures within a given grid.

528

529 Soil pH

530 We collected soil samples for the pH analysis from a subset of plots at the sites. In the high-

531 Arctic and low-Arctic sites, we collected 12 samples from each grid (in total 72 per site). In the

sub-Arctic, we collected 18 samples from each grid (in total 378). In the sub-Antarctic, we

collected between 16 and 39 samples per grid (in total 180). We estimated the pH values for the
remaining plots using bilinear interpolation. We forced the values between the minimum and
maximum of the laboratory measured soil pH within a given grid.

536

537 In the three Arctic sites, soil pH was determined from air-dried soil samples using distilled water 538 as a solution liquid following the International Organization for Standardization 10390:1994 (E) 539 protocol. The only difference in the protocol regarding the three Arctic sites was that the high-540 Arctic and low-Arctic samples were oven-dried, whereas the sub-Arctic samples were freeze dried. For the sub-Antarctic site, soil pH was determined from air-dried soil samples, measured 541 542 in calcium chloride solution (0.01 M). Calcium chloride in the solution increases dissolution of 543 H+ from soil particles to the measurement solution and measured pH values can be lower 544 compared to the pH values measured from soil-water solution ¹¹³. This may affect the 545 comparability of pH values between sub-Antarctic and Arctic sites, thus, we chose to analyse the 546 data using hierarchical generalized additive models, which enabled us to account for possible 547 minor differences between the sites.

548

549 Potential solar radiation

Incident radiation was calculated as the maximum potential solar radiation per plot (i.e. assuming
clear sky conditions) using field-quantified slope and aspect values of each plot for the Northern
Hemisphere ¹¹⁴ and for the Southern Hemisphere ¹¹⁵.

553

554 Coarse-scale variables

555	Data on annual mean air temperature (2 m above the soil surface) and annual precipitation at a
556	resolution of circa 1000 meters were downloaded from the Chelsa Climate database ¹¹⁶ . Potential
557	solar radiation was calculated using the ASTER Global Digital Elevation Model downloaded
558	from NASA's Land Processes Distributed Active Archive Center ¹¹⁷ . Data on soil pH in H ₂ O
559	solution at the resolution of 250 m were downloaded from the SoilGrids database ¹¹⁸ . The
560	Spearman's correlation between the field-quantified and coarse-scale environmental variables
561	were as follows: temperature 0.83, moisture 0.52, soil pH 0.48, and radiation 0.83. See Appendix
562	2 for comparison between results derived from the fine-scale and coarse-scale data.
563	
564	Statistical analysis
565	The environmental drivers showed weak collinearity (Spearman's correlations -0.31 to 0.42;

365 566 Appendix 9), thus, we included them all as predictors. All trait-environment relationships were 567 significant ($p \le 0.05$), except for three global relationships: leaf dry matter content and radiation (p = 0.90), leaf phosphorus and soil pH (p = 0.14), and specific leaf area and radiation (p = 0.12). 568 569

570 We analysed the data using hierarchical generalized additive models (Hierarchical GAMs or 571 HGAMs⁴⁹). The generalized additive model (GAM) is a flexible technique for modelling 572 outcomes as nonlinear functions of predictor variables. HGAMs are a conceptual extension of 573 GAMs, in a similar way that linear mixed models are an extension of linear models. HGAMs can 574 be used to study whether the functional relationship between response and predictor has the same 575 form for all levels of a grouping variable (in this study across the four sites). The relative 576 importance of the global relationship vs. site-specific deviations from the relationship for 577 explaining the response variable can then be assessed. We chose HGAMs as our modelling

approach because our data set is nested into four distinct study sites. We modelled the fine-scaleand coarse-scale models using the same methodology.

580

581 We fitted the HGAMs with the package mgcv version 1.8-24 ¹¹⁹, using the following command:

582 gam(response ~

583s(soil moisture, k=20)+ s(soil moisture, site, k=20, bs="fs")584+ s(soil temperature, k=20)+ s(soil temperature, site, k=20, bs="fs")

585 + s(soil pH, k=20) + s(soil pH, site, k=20, bs="fs")

586 + s(radiation, k=20) + s(radiation, site, k=20, bs="fs")

587 + s(site, grid, bs = "re"),

588 method="REML",

589 min.sp = c(rep(1,times=16),0))

590 Our model structure was as follows: for each environmental driver, we used a thin plate spline to 591 represent the global trait-environment relationship. Site-specific deviations from the global 592 relationship were included as simple factor-smooth interactions, where the site-specific splines 593 had the same wiggliness as the global splines. Here, the wiggliness of a spline refers to how quickly the function changes across its scale ⁴⁹. Each spline was constructed of 20 basis 594 595 functions. We also included a random intercept for each site-grid combination (i.e., a random 596 effect for each unique grid). To avoid overfitting, we specified that the smoothing parameters of 597 the environmental response splines must have a minimum value of 1. This choice was based on 598 visual evaluation of preliminary models and their smoothness parameters. Higher values of the 599 smoothing parameter mean less wiggly splines. Separate models were fitted for all traits using

restricted maximum likelihood (REML) estimation. We used R version 3.5.1 for all analyses and
 models ¹²⁰.

602

603 The fitted values of a GAM model are the sum of all splines (global, local, random intercept; 604 Table 1) and the model intercept. We quantified model fit as the squared correlation of observed 605 and fitted values (r²). We assessed the relative importance of global and local trait-environment 606 relationships by first subtracting the site-specific splines from the fitted values and noting the 607 decrease in r^2 . We then continued to subtract the global splines and again noted the decrease in r^2 . The sum of these decreases we interpret as the amount of variation explained by the 608 609 environment. We compared the relative magnitudes of these two values for each site-trait 610 combination to infer whether plant community functional trait composition is explained by 611 global or local trait-environment relationships (Figure 2).

612

We performed a principal component analysis (PCA) separately for the environmental and trait data (Appendix 3). Here, we used the package *FactoMineR* to scale the data to unit variance and derive the principal component scores for the first two components (PCA1 and PCA2) and the variable contributions ^{121,122}. Then, we calculated the Spearman's correlation between the components as follows: 1) environmental PCA1 and trait PCA1, 2) environmental PCA2 and trait PCA2, 3) environmental PCA1 and trait PCA2, and 4) environmental PCA2 and trait PCA1 (Appendix 4).

620

621 We assessed the relative importance of each environmental variable using HGAM (Appendix 5).

Here, we compared the model (full model) with sets of reduced models. In the latter, we

623	excluded one variable at a time from the full model. This exclusion comprised both the global			
624	and site-level terms of a given variable. Then, we compared the deviance explained of the full			
625	model and the reduced models to quantify how well including a given variable improved the			
626	prediction of the effect seen in the full model. In the reduced models, we used the same penalty			
627	terms as in the full model, to ensure that the reduced model did not only increase the flexibility			
628	of a term correlated with the excluded variable, which could have improved the fit of the model.			
629				
630	We repeated the HGAM analysis using coarse-scale climate and grid data instead of the fine-			
631	scale in situ data using the following command:			
632	gam(response ~			
633	s(soil moisture, k=10)			
634	+ s(soil temperature, k=10)			
635	+ s(soil pH, k=10)			
636	+ s(radiation, k=10)			
637	+ s(site, grid, bs = "re"),			
638	method="REML",			
639	min.sp = c(rep(1,times=4),0))			
640				
641	Data availability			

We have provided the reviewers the data. The data will be deposited in a public repository upon publication if the manuscript is accepted for publication.

645 <u>Code availability</u>

- 646 We have provided the reviewers the code. The code will be deposited in a public repository upon
- 647 publication if the manuscript is accepted for publication.

648 Appendix 1

656

environmental variables.

Appendix 1. Within-grid variation versus variability in the whole dataset. We calculated the amount of variation in each variable, which we measured as range and standard deviation of the environmental predictors and CWM traits within each of the 42 study grids and compared the variation to the whole data consisting all study sites. The values are averaged over all grids and separately for each study site. For instance, we found that soil moisture shows especially great within-grid variability, as on average a grid has approximately 50% of the variation of the entire dataset. Whereas, soil temperature displays the least within-grid variability of the four

```
All sites High-Arctic Low-Arctic Sub-Arctic Sub-Antarctic
```

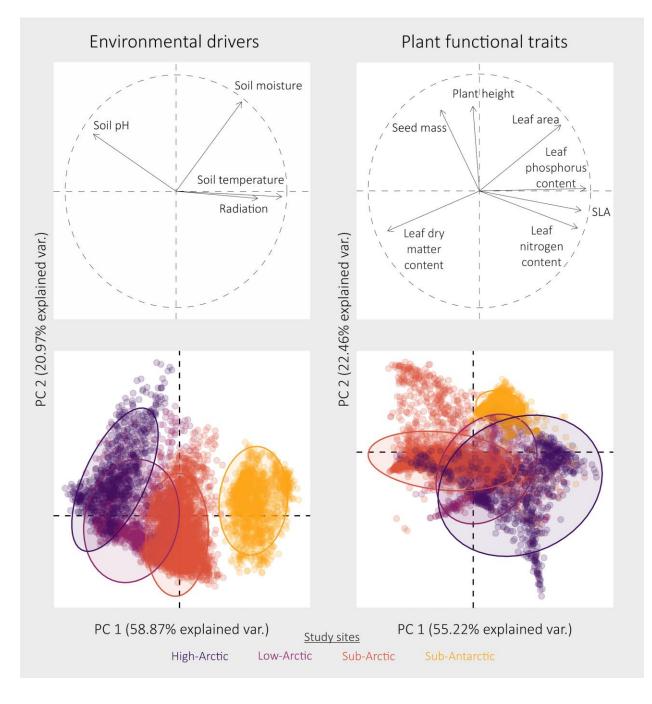
			Range		
Soil moisture	47.3	64.3	52.0	41.0	47.4
Soil temperature	17.3	25.3	26.4	16.1	8.9
Soil pH	31.3	32.4	41.0	29.3	28.8
Radiation	43.3	27.4	56.1	45.7	39.8
Leaf area	19.6	7.3	15.2	5.4	64.0
Plant height	44.9	23.9	75.9	47.5	32.2
Seed mass	35.6	11.4	7.6	59.2	15.2
Leaf dry matter content	37.1	60.7	48.4	34.4	20.4
Leaf nitrogen content	43.9	62.3	51.2	43.8	26.8
Lead phosphorus content	45.7	65.8	56.8	46.8	22.3
Specific leaf area	50.5	51.8	57.8	49.4	47.2

	Standard deviation				
Soil moisture	48.7	72.7	59.6	38.4	49.7
Soil temperature	16.4	27.8	23.0	14.7	8.3
Soil pH	36.1	36.9	50.4	34.3	30.1
Radiation	36.7	23.2	49.3	37.2	36.1
Leaf area	27.0	13.0	20.1	6.6	88.6
Plant height	63.7	34.7	142.8	61.7	35.3
Seed mass	56.5	24.8	12.9	89.6	29.4
Leaf dry matter content	35.5	54.6	43.3	34.9	18.8
Leaf nitrogen content	58.5	81.6	57.9	63.9	30.9
Lead phosphorus content	57.2	75.2	68.9	64.3	20.8
Specific leaf area	64.4	63.4	59.0	70.2	55.0

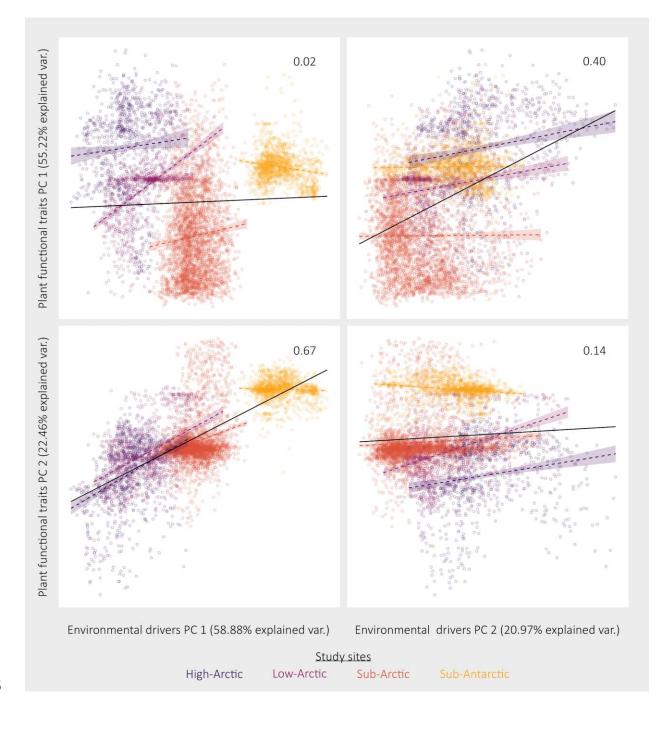
- 659 Appendix 2. Comparison of the results based on the fine-scale and coarse-scale data. Results
- based on the fine-scale data outperformed the coarse-scale for all seven plant functional traits.
- 661 The r^2 values for the models are divided between the random effect and the global trait-
- 662 environment relationship, and for the fine-scale data also the local trait-environment relationship.
- 663 The higher the value, the greater proportion explained by the factor.

Discrete tracite	Deviance explained (%)			Rando	Random effect		Global relationship		
Plant trait -	Fine-scale	Coarse-scale	- Site	Fine-scale	Coarse-scale	Fine-scale	Coarse-scale	Fine-scale	
	87.7	86.5	High-Arctic	0.22	0.32	0.35	0.04	0.03	
Leaf area			Low-Arctic	0.11	0.33	0.37	0.03	0.04	
Leafarea			Sub-Arctic	0.27	0.21	0.21	0.15	0.05	
			Sub-Antarctic	0.30	0.05	-0.01	0.06	0.06	
Plant height	54.2	48.5	High-Arctic	0.19	0.17	0.38	0.19	0.02	
			Low-Arctic	0.02	0.10	0.28	0.13	0.03	
			Sub-Arctic	0.18	0.00	0.00	0.22	0.08	
			Sub-Antarctic	0.32	0.43	0.03	0.01	0.02	
Seed mass		48.9	High-Arctic	0.12	0.14	0.35	0.02	0.03	
	55.6		Low-Arctic	0.05	0.17	0.14	0.01	0.17	
			Sub-Arctic	0.22	0.12	0.03	0.18	0.10	
			Sub-Antarctic	0.17	0.38	0.05	0.12	0.04	
	87.6	83.1	High-Arctic	0.42	0.46	0.18	0.03	0.03	
1 f day			Low-Arctic	0.20	0.36	0.24	0.01	0.05	
Leaf dry matter content			Sub-Arctic	0.19	0.21	0.20	0.09	0.09	
			Sub-Antarctic	0.35	0.28	0.03	0.11	0.18	
	69.5	59.9	High-Arctic	0.21	0.28	0.24	0.02	0.04	
Leaf nitrogen content			Low-Arctic	0.15	0.20	0.06	0.02	0.13	
Lear nitrogen content			Sub-Arctic	0.24	0.15	0.21	0.19	0.05	
			Sub-Antarctic	0.00	0.00	0.12	0.25	0.10	
Leaf phosphorus content	71.2	61.3	High-Arctic	0.34	0.41	0.24	0.01	0.05	
			Low-Arctic	0.19	0.29	0.16	0.01	0.14	
			Sub-Arctic	0.25	0.19	0.19	0.15	0.04	
			Sub-Antarctic	0.02	0.09	0.04	0.03	0.21	
Specific leaf area	65.0	57.0	High-Arctic	0.45	0.41	0.14	0.08	0.03	
			Low-Arctic	0.15	0.15	-0.03	0.02	0.10	
			Sub-Arctic	0.30	0.17	0.23	0.24	0.05	
			Sub-Antarctic	0.01	0.07	0.10	0.37	0.01	

665



Appendix 3. Principal component analysis of the environmental space and the plant functional trait space. The upper panels present the data distributed according to the environmental space (left) and the plant functional trait space (right). In the lower panels, the circles represent the 6720 study plots and the ellipsoids the sites in relation to the environmental space (left) and the plant functional trait space (right). The variation explained by each axis is shown in brackets. SLA = Specific leaf area.



677 Appendix 4. Linear relationships between principal components of the environmental and trait 678 space. The strongest correlations are found between 1) the primary axis of the environmental 679 drivers (representing mainly the mean annual soil temperature, soil pH, and potential solar 680 radiation) and the secondary axis of the traits (plant height, leaf area, and seed mass), and 681 between 2) their secondary axis (soil moisture) and primary axis (specific leaf area, leaf dry 682 matter content, leaf nitrogen content, and leaf phosphorus content). The circles represent the 683 6720 study plots. The values in the upper corners of the panels show the Spearman's correlation 684 between the plotted principal component (PC) axes. The black line represents a linear trend 685 across all sites, and the coloured within each site and the band the confidence interval of 0.95%. 686 See Appendix 3 for details.

688 Appendix 5. The relative importance of environmental drivers. We compared the full HGAM 689 model with sets of reduced models. In the latter, we excluded one environmental variable at a 690 time from the full model. This exclusion comprised both the global and site-level terms of a 691 given environmental variable. In the reduced models, we used the same penalty terms as in the 692 full model, to ensure that the reduced model did not only increase the flexibility of a term 693 correlated with the excluded variable, which could have improved the fit of the model. Variable 694 importance was assessed by repeating HGAM models after the exclusion of one environment 695 variable at a time. The values reported here are the deviance explained values for the reduced 696 models, with the lowest values for each trait indicating that a model performed worst after the 697 exclusion of that specific predictor variable. In other words, the lower the value, the higher the 698 relative importance of a given environmental variable. For example, soil temperature was 699 relatively the most important variable for most of the traits, except for plant height, for which 700 soil moisture was more important.

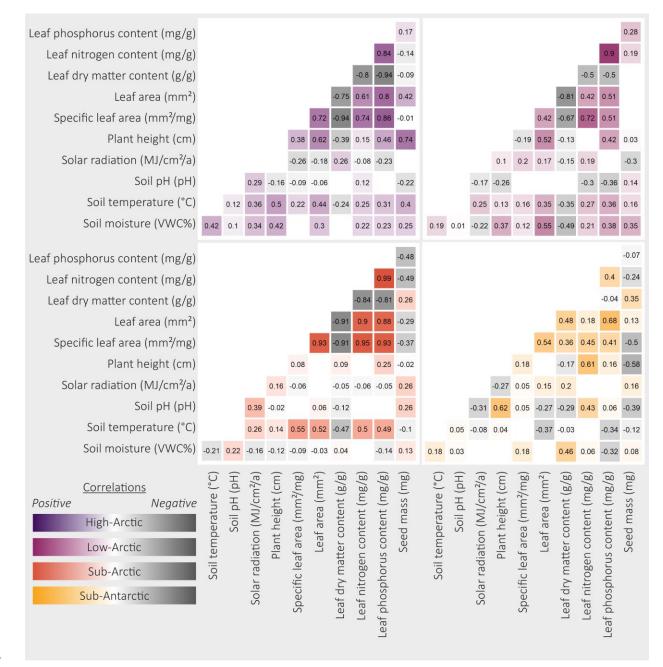
Plant trait	Soil moisture	Soil temperature	Soil pH	Solar radiation	
Leafarea	0.87	0.86	0.87	0.88	
Plant height	0.52	0.53	0.53	0.53	
Seed mass	0.55	0.54	0.54	0.54	
Leaf dry mass content	0.87	0.87	0.87	0.88	
Leaf nitrogen content	0.68	0.66	0.68	0.69	
Leaf phosphorus content	0.70	0.68	0.70	0.71	
Specific leaf area	0.63	0.60	0.64	0.65	

- 703 Appendix 6. Species list shows the presence and absence of the species in the study plots of the
- four study sites. The first row shows how many species were observed at each site. The last
- 705 column on the right shows in how many sites a given species was observed.

Species	High-Arctic	Low-Arctic	Sub-Arctic	Sub-Antarctic	Multiple sites	Species	High-Arctic	Low-Arctic	Sub-Arctic	Sub-Antarctic	Multiple site
In total = 217 species	61	75	134	18	88	opecies	Tign Areae	Low Arelie	Sub Arctic	Sub Antarctic	iviarcipie are
Acaena magellanica	0	0	0	1	1	Linnaea borealis	0	0	1	0	1
Achillea millefolium	õ	ō	1	ō	1	Luzula arctica	1	1	ō	ō	2
Agrostis mertensii	0	0	1	0	1	Luzula arcuata	0	0	1	0	1
Agrostis stolonifera	0	0	0	1	1	Luzula confusa Luzula multiflora	1	1	1	0	3 2
Alchemilla sp. Alopecurus magellanicus		0	1	0	1	Luzula multifiora Luzula parviflora	0	0	1	0	1
Andromeda polifolia	ō	0	1	0	1	Luzula spicata	0	0	1	0	1
Angelica archangelica	0	0	1	0	1	Luzula sudetica	0	0	1	0	1
Antennaria alpina	0	1	1	0	2	Luzula wahlenbergii Lycopodium clavatum	0	0	1	0	1
Antennaria canescens Antennaria dioica	0	0	1	0	1	Lysimachia europaea	0	0	1	0	1
Anthoxanthum monticol		1	1	0	2	Micranthes foliolosa	1	0	1	0	2
Anthoxanthum odoratum	0	0	1	0	1	Micranthes nivalis	1	0	1	0	2
Arctostaphylos uva.ursi Arctous alpina	0	0	1	0	1	Micranthes tenuis Montia fontana	1	0	0	0	1
Arctous alpina Artemisia borealis	0	1	0	0	1	Nardus stricta	0	0	1	0	1
Astragalus alpinus	ō	0	1	0	1	Neottia cordata	0	0	1	ō	1
Astragalus frigidus	0	0	1	0	1	Omalotheca norvegica	0	0	1	0	1
Austroblechnum penna r Austrolycopodium mage	0	0	0	1	1	Omalotheca supina Orthilia socunda	0	0	1	0	1
Austrolycopoulum mage. Avenella flexuosa	0	0	1	0	1	Orthilia secunda Oxyria digyna	1	1	1	0	3
Azorella selago	0	0	0	1	1	Papaver radicatum	1	0	0	0	1
Bartsia alpina	0	0	1	0	1	Parnassia palustris	0	0	1	0	1
Betula nana	0	1	1	0	2	Pedicularis dasyantha	0	1	0	0	1
Betula pubescens Bistorta vivipara	0	1	1	0	1	Pedicularis flammea Pedicularis hirsuta	1	0	0	0	1
Botrychium Iunaria	ō	ō	1	ō	1	Pedicularis lapponica	ō	1	1	ō	2
Calamagrostis canadensi	0	1	0	0	1	Phlegmariurus saururus	0	0	0	1	1
Calamagrostis lapponica		0	1	0	1	Phleum alpinum	0	0	1	0	1
Calamagrostis neglecta Campanula rotundifolia	0	1	0	0	1 2	Phyllodoce caerulea Pinguicula alpina	0	0	1	0	1
Cardamine bellidifolia	1	1	1	0	3	Pinguicula alpina Pinguicula vulgaris	0	0	1	0	1
Carex aquatilis	0	1	0	0	1	Poa alpigena	0	1	1	0	2
Carex arctogena	0	0	1	0	1	Poa alpina	1	1	1	0	3
Carex atrata Carex austrocompacta	0	0	1	0	1	Poa annua Poa arctica	0	0	0	1	1 3
Carex austrocompacta Carex bigelowii	0	1	0	1	1 2	Poa arctica Poa cookii	1	1	1	1	3
Carex canescens	0	1	1	0	2	Poa glauca	1	1	0	0	2
Carex capillaris	0	0	1	0	1	Poa nemoralis	0	0	1	0	1
Carex glacialis	0	1	0	0	1	Poa pratensis Polemonium boreale	1	0	0	1	2 1
Carex lachenalii Carex myosuroides	0	1	0	0	1	Polemonium boreale Polypogon magellanicus	0	0	0	1	1
Carex nardina	ō	1	0	0	1	Potentilla crantzii	0	0	1	0 0	1
Carex norvegica	0	0	1	0	1	Potentilla hyparctica	1	0	0	0	1
Carex panicea	0	0	1	0	1	Potentilla nivea	0	1	0	0	1
Carex parallela Carex rariflora	0	0	1	0	1	Pyrola grandiflora Pyrola minor	0	1	0	0	1
Carex rupestris	1	1	1	0	3	Pyrola rotundifolia	0	0	1	0	1
Carex saxatilis	0	1	0	0	1	Ranunculus acris	0	0	1	0	1
Carex supina	0	1	0	0	1	Ranunculus biternatus	0	0	0	1	1
Carex vaginata	0	0	1	0	1	Ranunculus nivalis	1	0	1	0	2
Cassiope tetragona Cerastium sp.	0	0	1	0	1	Ranunculus pygmaeus Ranunculus sulphureus	1	0	0	0	1
Cerastium alpinum	0	1	1	0	2	Rhodiola rosea	ō	0	1	0	1
Cerastium arcticum	1	0	0	0	1	Rhododendron lapponicu	0	1	1	0	2
Cerastium cerastoides	0	1	0	0	1	Rhododendron tomentos	0	1	0	0	1
Cerastium fontanum Cerastium regelii	1	0	0	0	1	Rubus saxatilis Rumex acetosa	0	0	1	0	1
Cherleria biflora	1	1	1	0	3	Sabulina rubella	1	1	0	0	2
Cystopteris fragilis	0	0	1	0	1	Sagina nivalis	1	0	0	0	1
Dactylorhiza viridis	0	0	1	0	1	Sagina procumbens	0	0	0	1	1
Deschampsia alpina Deschampsia cespitosa	1	0	1	0	1	Sagina saginoides Salix arctophila	0	1	0	0	1
Diapensia lapponica	ō	1	1	ō	2	Salix glauca	ō	1	1	õ	2
Diphasiastrum alpinum	0	0	1	0	1	Salix hastata	0	0	1	0	1
Draba sp.	0	1	0	0	1	Salix herbacea	0	1	1	0	2
Draba alpina Draba arctica	1	0	0	0	1	Salix lapponum Salix myrsinifolia	0	0	1	0	1
Draba fladnizensis	1	0	0	ō	1	Salix myrtilloides	0	0	1	o	1
Draba glabella	1	1	1	0	3	Salix phylicifolia	0	0	1	0	1
Draba lactea	1	0	0	0	1	Salix polaris	1	0	1	0	2
Draba micropetala Draba pivalia	1	0	0	0	1	Salix reticulata	0	0	1	0	1
Draba nivalis Draba norvegica	1	1	1	0	3 1	Saussurea alpina Saxifraga cernua	0	0	1	0	1 2
Draba pauciflora	1	0	0	0	1	Saxifraga cespitosa	1	ō	1	0	2
Draba subcapitata	1	0	0	0	1	Saxifraga hieracifolia	1	0	0	0	1
Dryas integrifolia	0	1	0	0	1	Saxifraga hirculus Saxifraga hyperborea	1	0	0	0	1 1
Dryas octopetala Empetrum nigrum	1	1	1	0	2	Saxifraga nyperborea Saxifraga oppositifolia	1	1	0	0	2
pilobium angustifolium		0	1	0	1	Saxifraga platysepala	1	0	0	0	1
Epilobium latifolium	0	1	0	0	1	Saxifraga rivularis	0	1	0	0	1
Equisetum arvense	1	1	0	0	2	Saxifraga svalbardensis	1	0	0	0	1
Equisetum palustre Equisetum pratense	0	0	1	0	1	Saxifraga tricuspidata Scorzoneroides autumna	0	1	0	0	1
Equisetum pratense Equisetum scirpoides	1	0	1	0	2	Selaginella selaginoides	0	0	1	0	1
quisetum variegatum	1	0	0	0	1	Sibbaldia procumbens	0	0	1	0	1
rigeron humilis	0	1	0	0	1	Silene acaulis	1	1	1	0	3
rigeron uniflorus riophorum angustifoliuu	0	0	1	0	1 2	Silene involucrata Silene suecica	1	1	0	0	2
riophorum angustifoliuı uphrasia wettsteinii	0	1	1	0	2	Silene uralensis	0	0	1	0	1
estuca brachyphylla	ō	1	0	0	1	Solidago virgaurea	0	0	1	ō	1
estuca edlundiae	1	0	0	0	1	Spinulum annotinum	0	0	1	0	1
estuca ovina	0	0	1	0	1 2	Stellaria humifusa	0	1	0	0	1 2
estuca rubra estuca viviparoidea	1	1	0	0	2	Stellaria longipes Taraxacum sp.	1	1	0	0	2
estaca viviparoidea Bentiana nivalis	0	0	1	0	1	Thalictrum alpinum	0	1	1	0	2
ieranium sylvaticum	0	0	1	ō	1	Tofieldia coccinea	0	1	0	0	1
frammitis poeppigiana	0	0	0	1	1	Tofieldia pusilla	0	1	1	0	2
larrimanella hypnoides	0	1	1	0	2	Trichophorum cespitosur	0	0	1	0	1
tieracium sp. tuperzia selago	0	0	1	0	1	Trisetum spicatum Vaccinium myrtillus	1	1	1	0	3 1
luperzia selago lymenophyllum peltatui		0	0	1	1	Vaccinium myrtillus Vaccinium uliginosum	0	1	1	0	2
uncus biglumis	1	1	1	0	3	Vaccinium vitis.idaea	0	1	1	0	2
uncus castaneus	0	1	0	0	1	Vahlodea atropurpurea	0	0	1	0	1
uncus scheuchzerioides	0	0	0	1	1	Veronica alpina	0	0	1	0	1
uncus trifidus	0	1	1	0	2	Veronica fruticans	0	0	1	0	1
uniperus communis	0	0	1	0	1	Viola biflora Woodsia alpina	0	0	1	0	1
Calmia procumbens											

- 708 Appendix 7. Full citation list of all sources regarding the plant functional traits data.
- 709 (Due to its large size, the list is attached as a separate PDF file for the convenience of the reader.)

- 711 Appendix 8. A comprehensive summary and basic statistics of the trait data. The table shows the
- coverage of the trait data and CWM bootstrapping estimates separated by study site and
- 713 functional trait.
- 714
- 715 (Due to its large size, the table is attached as a separate excel file for the convenience of the
- 716 reader.)



719 Appendix 9. Bivariate correlations. The correlation matrix shows the Spearman's correlations

- between variables (n = 6720). Statistically significant (P < 0.05) correlations are shown as
- squares, whereas non-significant correlations ($P \ge 0.05$) are blank.

722 References

- Shipley, B. *et al.* Reinforcing loose foundation stones in trait-based plant ecology. *Oecologia* 180, 923–931 (2016).
- McGill, B. J., Enquist, B. J., Weiher, E. & Westoby, M. Rebuilding community ecology from
 functional traits. *Trends Ecol. Evol.* 21, 178–185 (2006).
- 727 3. Vellend, M. Conceptual synthesis in community ecology. Q. Rev. Biol. 85, 183–206 (2010).
- 4. Bjorkman, A. D. *et al.* Plant functional trait change across a warming tundra biome. *Nature* 562, 57–62 (2018).
- 5. Billings, W. D. Arctic and Alpine Vegetations: Similarities, Differences, and Susceptibility to
 Disturbance. *BioScience* vol. 23 697–704 (1973).
- Graae, B. J. *et al.* Stay or go how topographic complexity influences alpine plant population and
 community responses to climate change. *Perspectives in Plant Ecology, Evolution and Systematics*vol. 30 41–50 (2018).
- 735 7. Bruelheide, H. *et al.* Global trait-environment relationships of plant communities. *Nat Ecol Evol* 2, 1906–1917 (2018).
- 737 8. Choler, P. Consistent Shifts in Alpine Plant Traits along a Mesotopographical Gradient. *Arctic*,
 738 *Antarctic, and Alpine Research* vol. 37 444–453 (2005).
- Wullschleger, S. D. *et al.* Plant functional types in Earth system models: past experiences and future
 directions for application of dynamic vegetation models in high-latitude ecosystems. *Ann. Bot.* 114,
- 741 1–16 (2014).
- 10. Pearson, R. G. *et al.* Shifts in Arctic vegetation and associated feedbacks under climate change.
- 743 *Nature Climate Change* vol. 3 673–677 (2013).
- Myers-Smith, I. H., Thomas, H. J. D. & Bjorkman, A. D. Plant traits inform predictions of tundra
 responses to global change. *New Phytol.* 221, 1742–1748 (2019).
- 12. Robinson, S. A. *et al.* Rapid change in East Antarctic terrestrial vegetation in response to regional

- 747 drying. Nature Climate Change vol. 8 879–884 (2018).
- 748 13. Post, E. *et al.* Ecological dynamics across the Arctic associated with recent climate change. *Science*749 **325**, 1355–1358 (2009).
- 14. Saros, J. E. *et al.* Arctic climate shifts drive rapid ecosystem responses across the West Greenland
 landscape. *Environ. Res. Lett.* 14, 074027 (2019).
- 15. Lavorel, S. & Garnier, E. Predicting changes in community composition and ecosystem functioning
 from plant traits: revisiting the Holy Grail. *Functional Ecology* vol. 16 545–556 (2002).
- 16. Chapin, F. S., 3rd *et al.* Consequences of changing biodiversity. *Nature* **405**, 234–242 (2000).
- 17. Díaz, S. *et al.* The global spectrum of plant form and function. *Nature* **529**, 167–171 (2016).
- 18. Wright, I. J. *et al.* The worldwide leaf economics spectrum. *Nature* **428**, 821–827 (2004).
- Thomas, H. J. D. *et al.* Global plant trait relationships extend to the climatic extremes of the tundra
 biome. *Nat. Commun.* 11, 1351 (2020).
- 759 20. Billings, W. D. & Bliss, L. C. An Alpine Snowbank Environment and Its Effects on Vegetation,

760 Plant Development, and Productivity. *Ecology* vol. 40 388–397 (1959).

- 761 21. Myers-Smith, I. H. & Hik, D. S. Shrub canopies influence soil temperatures but not nutrient
- dynamics: An experimental test of tundra snow-shrub interactions. *Ecol. Evol.* **3**, 3683–3700 (2013).
- 763 22. Chapin, F. S., 3rd *et al.* Role of land-surface changes in arctic summer warming. *Science* 310, 657–
 764 660 (2005).
- Cahoon, S. M. P. *et al.* Interactions among shrub cover and the soil microclimate may determine
 future Arctic carbon budgets. *Ecol. Lett.* 15, 1415–1422 (2012).
- 767 24. Reich, P. B. The world-wide 'fast-slow' plant economics spectrum: a traits manifesto. *Journal of*768 *Ecology* vol. 102 275–301 (2014).
- Diaz, S. *et al.* The plant traits that drive ecosystems: Evidence from three continents. *J. Veg. Sci.* 15, 295–304 (2004).
- 26. Cornelissen, J. H. C. *et al.* Global negative vegetation feedback to climate warming responses of leaf
 litter decomposition rates in cold biomes. *Ecol. Lett.* 10, 619–627 (2007).

- 27. Steinbauer, M. J. *et al.* Accelerated increase in plant species richness on mountain summits is linked
 to warming. *Nature* 556, 231–234 (2018).
- 775 28. Myers-Smith, I. H. *et al.* Climate sensitivity of shrub growth across the tundra biome. *Nat. Clim.*776 *Chang.* 5, 887–891 (2015).
- 29. Post, E. *et al.* The polar regions in a 2°C warmer world. *Sci. Adv.* **5**, eaaw9883 (2019).
- 30. Intergovernmental Panel on Climate Change. Global Warming of 1.5°C: An IPCC Special Report on
- the Impacts of Global Warming of 1.5°C Above Pre-industrial Levels and Related Global
- 780 *Greenhouse Gas Emission Pathways, in the Context of Strengthening the Global Response to the*
- 781 Threat of Climate Change, Sustainable Development, and Efforts to Eradicate Poverty. (2018).
- 31. Bintanja, R. & Andry, O. Towards a rain-dominated Arctic. *Nature Climate Change* vol. 7 263–267
 (2017).
- 32. Bromwich, D. H. *et al.* Central West Antarctica among the most rapidly warming regions on Earth.
 Nature Geoscience vol. 6 139–145 (2013).
- 786 33. Turner, J. *et al.* Absence of 21st century warming on Antarctic Peninsula consistent with natural
 787 variability. *Nature* 535, 411–415 (2016).
- Sonesson, M., Wielgolaski, F. E. & Kallio, P. Description of Fennoscandian Tundra Ecosystems.
 Ecological Studies 3–28 (1975) doi:10.1007/978-3-642-80937-8_1.
- 790 35. Niittynen, P., Heikkinen, R. K. & Luoto, M. Snow cover is a neglected driver of Arctic biodiversity
 791 loss. *Nature Climate Change* vol. 8 997–1001 (2018).
- 36. Klikoff, L. G. Photosynthetic Response to Temperature and Moisture Stress of Three Timberline
 Meadow Species. *Ecology* vol. 46 516–517 (1965).
- 794 37. Oberbauer, S. F. & Billings, W. D. Drought tolerance and water use by plants along an alpine
 795 topographic gradient. *Oecologia* 50, 325–331 (1981).
- 796 38. Eskelinen, A., Stark, S. & Männistö, M. Links between plant community composition, soil organic
- matter quality and microbial communities in contrasting tundra habitats. *Oecologia* vol. 161 113–
- 798 123 (2009).

- 39. Ernakovich, J. G. *et al.* Predicted responses of arctic and alpine ecosystems to altered seasonality
 under climate change. *Glob. Chang. Biol.* 20, 3256–3269 (2014).
- 40. Galen, C. & Stanton, M. L. Responses of Snowbed Plant Species to Changes in Growing-Season
 Length. *Ecology* vol. 76 1546–1557 (1995).
- 803 41. Starr, G., Oberbauer, S. F. & Ahlquist, L. E. The Photosynthetic Response of Alaskan Tundra Plants
 804 to Increased Season Length and Soil Warming. *Arctic, Antarctic, and Alpine Research* vol. 40 181–
 805 191 (2008).
- 42. Happonen, K. *et al.* Snow is an important control of plant community functional composition in
 oroarctic tundra. *Oecologia* vol. 191 601–608 (2019).
- 808 43. Niittynen, P. & Luoto, M. The importance of snow in species distribution models of arctic
- 809 vegetation. *Ecography* vol. 41 1024–1037 (2018).
- 44. le Roux, P. C., Aalto, J. & Luoto, M. Soil moisture's underestimated role in climate change impact
 modelling in low-energy systems. *Global Change Biology* vol. 19 2965–2975 (2013).
- 812 45. Lembrechts, J. J. *et al.* SoilTemp: a global database of near-surface temperature. *Glob. Chang. Biol.*
- 813 (2020) doi:10.1111/gcb.15123.
- 814 46. Bjorkman, A. D. *et al.* Tundra Trait Team: A database of plant traits spanning the tundra biome:
 815 XXXX. *Glob. Ecol. Biogeogr.* 27, 1402–1411 (2018).
- 816 47. Maitner, B. S. *et al.* The bien r package: A tool to access the Botanical Information and Ecology
 817 Network (BIEN) database. *Methods Ecol. Evol.* 9, 373–379 (2018).
- 818 48. Kattge, J. et al. TRY a global database of plant traits. Glob. Chang. Biol. 17, 2905–2935 (2011).
- 49. Pedersen, E. J., Miller, D. L., Simpson, G. L. & Ross, N. Hierarchical generalized additive models in
 ecology: an introduction with mgcv. *PeerJ* 7, e6876 (2019).
- 821 50. Niittynen, P. *et al.* Fine-scale tundra vegetation patterns are strongly related to winter thermal
- 822 conditions. *Nature Climate Change* (2020) doi:10.1038/s41558-020-00916-4.
- 823 51. Belluau, M. & Shipley, B. Predicting habitat affinities of herbaceous dicots to soil wetness based on
- physiological traits of drought tolerance. Ann. Bot. **119**, 1073–1084 (2017).

- 52. Kemppinen, J., Niittynen, P., Riihimäki, H. & Luoto, M. Modelling soil moisture in a high-latitude
 landscape using LiDAR and soil data: Soil moisture and LiDAR in a high-latitude landscape. *Earth Surf. Processes Landforms* 43, 1019–1031 (2018).
- Kemppinen, J., Niittynen, P., Aalto, J., le Roux, P. C. & Luoto, M. Water as a resource, stress and
 disturbance shaping tundra vegetation. *Oikos* vol. 128 811–822 (2019).
- S4. Giblin, A. E., Nadelhoffer, K. J., Shaver, G. R., Laundre, J. A. & McKerrow, A. J. Biogeochemical
 Diversity Along a Riverside Toposequence in Arctic Alaska. *Ecological Monographs* vol. 61 415–
- 832 435 (1991).
- 833 55. le Roux, P. C., Virtanen, R. & Luoto, M. Geomorphological disturbance is necessary for predicting
 834 fine-scale species distributions. *Ecography* vol. 36 800–808 (2013).
- 835 56. Finger Higgens, R., Hicks Pries, C. & Virginia, R. A. Trade-offs Between Wood and Leaf
- 836 Production in Arctic Shrubs Along a Temperature and Moisture Gradient in West Greenland.

837 *Ecosystems* (2020) doi:10.1007/s10021-020-00541-4.

- 838 57. Porporato, A. & Rodriguez-Iturbe, I. Ecohydrology-a challenging multidisciplinary research
- 839 perspective / Ecohydrologie: une perspective stimulante de recherche multidisciplinaire.
- 840 *Hydrological Sciences Journal* vol. 47 811–821 (2002).
- 58. Legates, D. R. *et al.* Soil moisture: A central and unifying theme in physical geography. *Progress in Physical Geography: Earth and Environment* vol. 35 65–86 (2011).
- 843 59. McLaughlin, B. C. *et al.* Hydrologic refugia, plants, and climate change. *Glob. Chang. Biol.* 23,
 844 2941–2961 (2017).
- 845 60. Choler, P. Winter soil temperature dependence of alpine plant distribution: Implications for
- 846 anticipating vegetation changes under a warming climate. *Perspectives in Plant Ecology, Evolution*847 *and Systematics* vol. 30 6–15 (2018).
- 848 61. Happonen, K. *et al.* Snow is an important control of plant community functional composition.
 849 doi:10.1101/564583.
- 850 62. Doran, P. T. *et al.* Antarctic climate cooling and terrestrial ecosystem response. *Nature* **415**, 517–520

851 (2002).

- 852 63. French, D. D. & Smith, V. R. A comparison between Northern and Southern Hemisphere tundras
 853 and related ecosystems. *Polar Biology* vol. 5 5–21 (1985).
- 854 64. le Roux, P. C. Climate and climate change. *The Prince Edward Islands: Land-Sea Interactions in a*855 *Changing Ecosystem.* 39–64 (2008) doi:10.18820/9781928357063/03.
- 856 65. Devau, N., Le Cadre Edith, Jaillarda, B. & Gérarda, F. Soil pH controls the environmental
- 857 availability of phosphorus: Experimental and mechanistic modelling approaches. *Appl. Geochem.*858 (2009) doi:S0883292709002625.
- 859 66. Stevens, R. J., Laughlin, R. J. & Malone, J. P. Soil pH affects the processes reducing nitrate to
 860 nitrous oxide and di-nitrogen. *Soil Biology and Biochemistry* vol. 30 1119–1126 (1998).
- 861 67. Freschet, G. T., Cornelissen, J. H. C., Van Logtestijn, R. S. P. & Aerts, R. Evidence of the 'plant
 862 economics spectrum' in a subarctic flora. *J. Ecol.* 98, 362–373 (2010).
- 863 68. Bergholz, K. *et al.* Fertilization affects the establishment ability of species differing in seed mass via
- direct nutrient addition and indirect competition effects. *Oikos* **124**, 1547–1554 (2015).
- 865 69. Curtin, D., Campbell, C. A. & Jalil, A. Effects of acidity on mineralization: pH-dependence of
- 866 organic matter mineralization in weakly acidic soils. *Soil Biol. Biochem.* **30**, 57–64 (1998).
- 867 70. Blondeel, H. *et al.* Light and warming drive forest understorey community development in different
 868 environments. *Glob. Chang. Biol.* 26, 1681–1696 (2020).
- 869 71. Dahlgren, J. P., Eriksson, O., Bolmgren, K., Strindell, M. & Ehrlén, J. Specific leaf area as a superior
- 870 predictor of changes in field layer abundance during forest succession. J. Veg. Sci. 17, 577–582
- 871 (2006).
- 872 72. Lembrechts, J. J. *et al.* Comparing temperature data sources for use in species distribution models:
 873 From in-situ logging to remote sensing. *Glob. Ecol. Biogeogr.* 28, 1578–1596 (2019).
- 874 73. Körner, C. & Hiltbrunner, E. The 90 ways to describe plant temperature. *Perspectives in Plant*
- 875 *Ecology, Evolution and Systematics* vol. 30 16–21 (2018).
- 876 74. Maclean, I. M. D. Predicting future climate at high spatial and temporal resolution. *Glob. Chang.*

- 877 *Biol.* (2019) doi:10.1111/gcb.14876.
- 878 75. De Frenne, P. *et al.* Global buffering of temperatures under forest canopies. *Nat Ecol Evol* 3, 744–
 879 749 (2019).
- 880 76. Aalto, J., Scherrer, D., Lenoir, J., Guisan, A. & Luoto, M. Biogeophysical controls on soil-
- atmosphere thermal differences: implications on warming Arctic ecosystems. *Environmental*
- 882 *Research Letters* vol. 13 074003 (2018).
- 77. Aalto, J., le Roux, P. C. & Luoto, M. Vegetation Mediates Soil Temperature and Moisture in ArcticAlpine Environments. *Arctic, Antarctic, and Alpine Research* vol. 45 429–439 (2013).
- 78. Moles, A. T. *et al.* Which is a better predictor of plant traits: temperature or precipitation? *Journal of Vegetation Science* vol. 25 1167–1180 (2014).
- 79. Taylor, R. V. & Seastedt, T. R. Short- and Long-Term Patterns of Soil Moisture in Alpine Tundra. *Arctic and Alpine Research* vol. 26 14 (1994).
- 889 80. Lembrechts, J. J. & Lenoir, J. Microclimatic conditions anywhere at any time! *Glob. Chang. Biol.*890 (2019) doi:10.1111/gcb.14942.
- 891 81. Zellweger, F., De Frenne, P., Lenoir, J., Rocchini, D. & Coomes, D. Advances in Microclimate
- Ecology Arising from Remote Sensing. *Trends Ecol. Evol.* **34**, 327–341 (2019).
- 893 82. Bramer, I. *et al.* Advances in Monitoring and Modelling Climate at Ecologically Relevant Scales.
- 894 *Next Generation Biomonitoring: Part 1* 101–161 (2018) doi:10.1016/bs.aecr.2017.12.005.
- 895 83. Halbritter, A. H. *et al.* The handbook for standardized field and laboratory measurements in
- terrestrial climate change experiments and observational studies (ClimEx). *Methods Ecol. Evol.* 2,
 16147 (2019).
- 898 84. Wild, J. et al. Climate at ecologically relevant scales: A new temperature and soil moisture logger
- for long-term microclimate measurement. *Agricultural and Forest Meteorology* vol. 268 40–47
 (2019).
- 901 85. Aalto, J., Riihimäki, H., Meineri, E., Hylander, K. & Luoto, M. Revealing topoclimatic
- 902 heterogeneity using meteorological station data. *International Journal of Climatology* vol. 37 544–

903 556 (2017).

- 904 86. Kearney, M. R., Gillingham, P. K., Bramer, I., Duffy, J. P. & Maclean, I. M. D. A method for
- 905 computing hourly, historical, terrain-corrected microclimate anywhere on earth. *Methods in Ecology*
- 906 *and Evolution* (2019) doi:10.1111/2041-210x.13330.
- 87. Bjorkman, A. D. *et al.* Status and trends in Arctic vegetation: Evidence from experimental warming
 and long-term monitoring. *Ambio* 23, 4294 (2019).
- 88. Vandvik, V., Halbritter, A. H. & Telford, R. J. Greening up the mountain. *Proceedings of the National Academy of Sciences of the United States of America* vol. 115 833–835 (2018).
- 911 89. Barnett, T. P., Adam, J. C. & Lettenmaier, D. P. Potential impacts of a warming climate on water
- 912 availability in snow-dominated regions. *Nature* **438**, 303–309 (2005).
- 90. Bring, A. *et al.* Arctic terrestrial hydrology: A synthesis of processes, regional effects, and research
 challenges. *J. Geophys. Res. Biogeosci.* 121, 621–649 (2016).
- 915 91. Bintanja, R. The impact of Arctic warming on increased rainfall. Sci. Rep. 8, 16001 (2018).
- 916 92. Smol, J. P. & Douglas, M. S. V. Crossing the final ecological threshold in high Arctic ponds. *Proc.*
- 917 Natl. Acad. Sci. U. S. A. 104, 12395–12397 (2007).
- 918 93. Higgens, R. A. F. *et al.* Changing Lake Dynamics Indicate a Drier Arctic in Western Greenland.
- 919 *Journal of Geophysical Research: Biogeosciences* vol. 124 870–883 (2019).
- 920 94. Nitze, I. *et al.* Landsat-Based Trend Analysis of Lake Dynamics across Northern Permafrost
 921 Regions. *Remote Sensing* vol. 9 640 (2017).
- 922 95. Roach, J. K. & Griffith, B. Climate-induced lake drying causes heterogeneous reductions in
- 923 waterfowl species richness. *Landscape Ecology* vol. 30 1005–1022 (2015).
- 924 96. Bonfils, C. J. W. *et al.* On the influence of shrub height and expansion on northern high latitude
 925 climate. *Environmental Research Letters* vol. 7 015503 (2012).
- 926 97. Zwieback, S., Chang, Q., Marsh, P. & Berg, A. Shrub tundra ecohydrology: rainfall interception is a
- 927 major component of the water balance. *Environmental Research Letters* vol. 14 055005 (2019).
- 928 98. Robinson, D. A. et al. Global environmental changes impact soil hydraulic functions through

- 929 biophysical feedbacks. *Glob. Chang. Biol.* **25**, 1895–1904 (2019).
- 930 99. Loranty, M. M. et al. Reviews and syntheses: Changing ecosystem influences on soil thermal
- 931 regimes in northern high-latitude permafrost regions. *Biogeosciences* vol. 15 5287–5313 (2018).
- 932 100. Parker, T. C., Subke, J.-A. & Wookey, P. A. Rapid carbon turnover beneath shrub and tree
- 933 vegetation is associated with low soil carbon stocks at a subarctic treeline. *Glob. Chang. Biol.* **21**,
- 934 2070–2081 (2015).
- 935 101. DeMarco, J., Mack, M. C. & Bret-Harte, M. S. Effects of arctic shrub expansion on biophysical vs.
 936 biogeochemical drivers of litter decomposition. *Ecology* 95, 1861–1875 (2014).
- 937 102. Qian, H., Joseph, R. & Zeng, N. Enhanced terrestrial carbon uptake in the Northern High Latitudes
- 938 in the 21st century from the Coupled Carbon Cycle Climate Model Intercomparison Project model
 939 projections. *Global Change Biology* vol. 16 641–656 (2010).
- 940 103. Sistla, S. A. *et al.* Long-term warming restructures Arctic tundra without changing net soil carbon
 941 storage. *Nature* 497, 615–618 (2013).
- 942 104. Norwegian Centre for Climate Services. *Climate in Svalbard 2100 a knowledge base for climate*943 *adaptation*. (2019).
- 944 105. Danish Meteorological Institute. Weather observations from Greenland 1958-2018 Observation
 945 data with description. (2019).
- 946 106. Finnish Meteorological Institute. Enontekiö Kilpisjärvi Saana. Daily climate observations (2019).
- 947 107. Finnish Meteorological Institute. Enontekiö Kilpisjärvi kyläkeskus. *Daily climate observations*948 (2019).
- 949 108. Smith, V. R. & Steenkamp, M. Classification of the terrestrial habitats on Marion Island based on
 950 vegetation and soil chemistry. *Journal of Vegetation Science* vol. 12 181–198 (2001).
- 951 109. Beck, H. E. *et al.* Present and future Köppen-Geiger climate classification maps at 1-km resolution.
 952 *Sci Data* 5, 180214 (2018).
- 953 110. Canadell, J. et al. Maximum rooting depth of vegetation types at the global scale. Oecologia 108,
- 954 583–595 (1996).

- 955 111. Iversen, C. M. et al. The unseen iceberg: plant roots in arctic tundra. New Phytol. 205, 34–58 (2015).
- 956 112. Kern, R. et al. Comparative vegetation survey with focus on cryptogamic covers in the high Arctic
- along two differing catenas. *Polar Biol.* **42**, 2131–2145 (2019).
- 958 113. Miller, R. O. & Kissel, D. E. Comparison of Soil pH Methods on Soils of North America. Soil
- 959 Science Society of America Journal vol. 74 310 (2010).
- 960 114. McCune, B. & Keon, D. Equations for potential annual direct incident radiation and heat load.
- 961 *Journal of Vegetation Science* vol. 13 603 (2002).
- 962 115. McCune, B. Improved estimates of incident radiation and heat load using non- parametric regression
- against topographic variables. *Journal of Vegetation Science* vol. 18 751 (2007).
- 116. Karger, D. N. *et al.* Climatologies at high resolution for the earth's land surface areas. *Scientific*Data vol. 4 (2017).
- 966 117. NASA's Land Processes Distributed Active Archive Center. ASTER Global Digital Elevation
 967 Model (GDEM) Version 3 (ASTGTM). doi:10.5067/ASTER/ASTGTM.003.
- 968 118. Hengl, T. *et al.* SoilGrids250m: Global gridded soil information based on machine learning. *PLoS*969 *One* 12, e0169748 (2017).
- 970 119. Wood, S. N. Generalized Additive Models. (2017) doi:10.1201/9781315370279.
- 971 120. R Core Team. *R: A language and environment for statistical computing. R Foundation for Statistical*972 *Computing, Vienna, Austria.* (2018).
- 973 121. Husson, F., Le, S. & Pagès, J. *Exploratory Multivariate Analysis by Example Using R*. (CRC Press,
 974 2017).
- 975 122. Lê, S., Josse, J. & Husson, F. FactoMineR: AnRPackage for Multivariate Analysis. *Journal of*976 *Statistical Software* vol. 25 (2008).

977