

1 **Plant traits poorly predict winner and loser shrub species in**

2 **a warming tundra biome**

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97

98 **Data archiving statement**

99 Code and data will be made available at the time of publication in an open-access
100 repository (GitHub) and have a DOI number assigned through Zenodo.

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106 **Abstract**

107 Climate change is leading to a species redistributions. In the tundra biome, many
108 shrub species are expanding into new areas, a process known as shrubification.
109 However, not all tundra shrub species will benefit from warming. Winner and loser
110 species (those projected to expand and contract their ranges, and/or those that have
111 increased or decreased in cover over time), and the characteristics that may determine
112 success or failure, have not been fully identified. Here, we investigate whether current
113 range sizes are related to plant trait values and intraspecific trait variation by
114 combining 17,921 trait records and distribution data from 62 shrub species across
115 three continents (>30 degrees north). In addition, we determine which traits are
116 associated with species projected by species distribution models to expand or contract
117 their ranges under climate change, and species that have undergone past cover
118 changes over time. Winner and loser shrub species identified from projected range
119 shifts generally differed from those identified from observed past cover change. We
120 found that greater variation in seed mass and specific leaf area were related to larger
121 projected range shifts. Projected winner species generally had greater seed mass
122 values than 'no change' and loser species. However, contrary to our expectations,
123 traits' values and variation were not consistently related to current and projected
124 ranges, and depended upon the future climate scenarios considered in range
125 projections. There were no clear relationships either between cover change over time
126 and trait values or variation. Overall, our findings indicate that abundance changes
127 and projected range shifts will not lead to directional modifications in shrub trait
128 composition or variation with future warming, since winner and loser species share
129 relatively similar trait spaces based on commonly measured traits. Future research

130 could investigate other morpho-physiological traits underpinning climatic preferences,
131 which might better predict future range and abundance changes.

132

133 **Keywords**

134 Climate change, traits, global change ecology, intraspecific trait variation, range
135 dynamics, species abundances, species distributions, tundra biome.

136

137

138 **Introduction**

139 The Arctic is warming at three to four times the rate of the global average (Chylek et
140 al., 2022; Rantanen et al., 2022), resulting in reported shifts in biodiversity and
141 changes in ecological processes. In particular, the phenomenon of ‘shrubification’ has
142 been extensively described across the tundra biome (García Criado et al., 2020;
143 Martin et al., 2017; Myers-Smith, Forbes, et al., 2011; Naito & Cairns, 2011; Sturm,
144 Racine, et al., 2001; Tape et al., 2006), with shrub species experiencing faster growth
145 and reproduction, increases in height (Forbes et al., 2010; Macias-Fauria et al., 2012)
146 and expanding into new areas (Myers-Smith, Forbes, et al., 2011; Pellissier et al.,
147 2010; Sturm, Racine, et al., 2001). These processes may cause reshuffling of species
148 compositions and functional diversity, thus affecting ecosystem function for the tundra
149 region and surrounding vegetation through biotic interactions (Alexander et al., 2015;
150 Mod et al., 2016; Niittynen et al., 2020). Despite shrubs’ dominance increase over
151 other functional groups, both increasing and decreasing shrub cover have been
152 reported at certain sites (Hollister et al., 2005; Maliniemi et al., 2018), and we do not
153 yet know whether expanding and contracting shrub species share similar traits.

154

155 Shifts in traits at the community level have already been observed, with taller species
156 spreading in a warming Arctic (Bjorkman, Myers-Smith, et al., 2018). However, the
157 biome-level relationships between trait values and intraspecific variation for a given
158 species and its geographic distribution have yet to be quantified for tundra shrub
159 species. These biome-scale relationships could dictate why some shrub species are
160 expanding/increasing (winners) and others are contracting/decreasing (losers), and
161 whether some species are not changing. Different methods to monitor species exist,
162 but in this study we compare two different scales: past changes in cover over time in

163 monitoring plots, and biome-scale projections of species ranges using species
164 distribution models (SDMs); two metrics that are generally positively related as per the
165 abundance-range size theory (Gaston & Blackburn, 2008).

166

167 The pattern of species moving polewards and towards higher elevations by tracking
168 warming temperatures has been discussed for over two decades (Chen et al., 2011;
169 Hastings et al., 2020; Hickling et al., 2006; Parmesan et al., 1999). Tundra species
170 distributions are the result of long-term glacial history and inherent Arctic geography.
171 Palaeoecological evidence indicates shrub expansion into the Arctic during the
172 warmer Last Interglacial and the Holocene post-glacial period (Birks, 2008; Crump et
173 al., 2021; Higuera et al., 2008), signalling that rising temperatures are likely to result
174 in further shrub expansion across the tundra (Gałka et al., 2018). Current range shifts
175 are mediated by processes derived by climate change including permafrost thaw and
176 extended season length (Sturm, Holmgren, et al., 2001), and factors like snow cover,
177 nutrient availability and species interactions, but also by the amount of potential habitat
178 and species' colonization capabilities. These, in turn, are determined by reproduction,
179 dispersal and establishment success – which could favour generalist species with
180 greater dispersal ability, reproductive rate, and competitive ability to expand into new
181 areas (Alsos et al., 2007; Angert et al., 2011; Venn et al., 2021). For instance, dwarf
182 birch (*Betula nana*) and tall willow (*Salix* sp.) species are expanding across the tundra
183 due to their flexible colonization strategy featuring clonal growth and high seed
184 dispersal capacity, respectively (Andruko et al., 2020; Formica et al., 2014; Myers-
185 Smith, Hik, et al., 2011; Ropars & Boudreau, 2012). Thus, certain traits could most
186 likely influence whether tundra species will expand or contract under climate change.

187

188 Plant traits have been widely used to assess species relationships with their
189 environment (Violle et al., 2007). As traits vary across environmental gradients, they
190 can be indicators of plant responses to climatic conditions (Díaz et al., 2016; Shipley
191 et al., 2016; Soudzilovskaia et al., 2013) and represent relevant dimensions of
192 functional and strategic variation between plant species (Pollock et al., 2012), at both
193 species and community levels (Bruehlheide et al., 2018). Plant traits are linked not only
194 to environmental responses but also to ecosystem functions like carbon storage and
195 nutrient cycling (Aubin et al., 2016; Lavorel & Garnier, 2002). Typically, trait-based
196 analyses use a single mean trait value per species at the global level (Violle et al.,
197 2007), disregarding individual variability information (Betway, Hollister, May, Harris, et
198 al., 2021; Bolnick et al., 2011; Myers-Smith, Thomas, et al., 2019; Siefert et al., 2015;
199 Thomas et al., 2019, 2020). Trait variation between and within populations can be
200 markedly different (Lamy et al., 2011), and is ultimately driven by differences among
201 individuals, rather than between species (Siefert et al., 2015). Thus, intraspecific trait
202 variation (ITV) might have a stronger influence on ecological dynamics than previously
203 thought (Bolnick et al., 2011; Jessen et al., 2020). However, ITV has not been
204 extensively accounted for in trait-based ecology (Moran et al., 2016), despite
205 accounting for 25% of total trait variation within communities, 32% among communities
206 (Siefert et al., 2015), and 23% of trait variation in tundra biome-wide data (Thomas et
207 al., 2020).

208

209 Traits that are related to dispersal, colonisation and growth can provide insights into
210 which species are more likely to expand or contract their ranges as the climate
211 changes. A trait framework that represents major axes of plant life history variation is
212 the leaf-height-seed strategy scheme defined by Westoby (1998), which describes a

213 plant's strategy based on its specific leaf area (SLA), plant height and seed mass.
214 Plant height relates to competitive ability, with tall plants shading out shorter
215 competitors. SLA is linked to carbon investment per area of light capture, and plants
216 with greater SLA obtain nutrients more easily. Seed mass is related to dispersal and
217 colonisation abilities because lighter seeds generally travel further, though larger
218 seeds tend to have higher germination success and seedling survival (Hamilton et al.,
219 2005). In the tundra, resource economics traits occupy much of the global trait space,
220 while structural traits such as plant height are relatively more restricted (Thomas et al.,
221 2020; Wright et al., 2004). Nevertheless, shrub species still show large relative
222 variability, reaching maximum heights of up to 3-4m among the species included in
223 this study. Since traits can explain species' responses to biotic and abiotic factors and
224 influence their competitive ability (Aubin et al., 2016; Lavorel & Garnier, 2002), we
225 would also expect traits to influence how species' distributions change in a warming
226 climate.

227

228 Species Distribution Models (SDMs) have arisen as a flexible tool to quantify current
229 species ranges and project their potential range shifts by combining species
230 occurrences with geospatial information on current and future climate variation
231 (Guisan & Thuiller, 2005; Thuiller et al., 2019). However, SDMs have been criticised
232 for their failure to incorporate evolutionary history, biotic interactions, or realistic
233 dispersal. Thus, range projections cannot fully reflect future species distributions in the
234 same way as collected range change data over time (Dormann, 2007; Pearson &
235 Dawson, 2003). Moreover, SDMs are correlative methods where the outcomes are
236 based on statistical relationships among variables and an assumption that species are
237 currently in equilibrium. Nonetheless, SDMs still provide useful estimates of potential

238 future suitable habitat in the absence of observational data (Elith & Leathwick, 2009),
239 and some SDMs now incorporate dispersal ability and additional parameters such as
240 morpho-physiological traits and their phenotypic plasticity to improve projections, thus
241 making more realistic future predictions (Chardon et al., 2020; Cunze et al., 2013;
242 Fordham et al., 2012; Garzón et al., 2019; Normand et al., 2013; Pollock et al., 2012).
243 If the processes of survival, reproduction, dispersal and colonisation determine a
244 plant's range, then range shifts should be associated with species' traits related to
245 these processes. In the warming tundra biome, community composition (Elmendorf et
246 al., 2012; Myers-Smith, Forbes, et al., 2011; M. D. Walker et al., 2006) and certain
247 size-related and resource economics traits are changing across time and space
248 (Bjorkman, Myers-Smith, et al., 2018; Thomas et al., 2020). However, the relationships
249 between species' traits and their current range size or potential for range shifts have
250 not been explored.

251

252 In this study, we combine species trait, range and abundance data to understand
253 whether median trait values (MTV) and intraspecific trait variation (ITV) are associated
254 with current range sizes in tundra shrubs. Additionally, we determine which categorical
255 and continuous traits are associated with species projected to expand or decrease
256 their ranges, and that have increased or decreased in abundance over time.
257 Considering the magnitude of observed vegetation changes in tundra ecosystems,
258 plant traits could be a particularly relevant tool to understand range dynamics across
259 a warming Arctic. Here, we address the following questions:

260

261 1) *Can traits explain current shrub species range sizes?*

262 Greater height and SLA are linked to competitive ability and resource acquisition (Díaz
263 et al., 2016), and small-seeded species are associated with longer dispersal and
264 greater seed production (Hamilton et al., 2005). Thus, we expect taller shrubs with
265 greater SLA values and lower seed mass to have the largest current range sizes. We
266 hypothesise that ITV in all three traits is positively related to species' range sizes, since
267 they could reflect greater adaptations to environmental variability. Greater genetic or
268 phenotypic variation could provide more scope for natural selection and adaptation
269 (Bolnick et al., 2011) and thus potentially increase species' chances of adapting to
270 diverse and fluctuating environmental conditions (Kumordzi et al., 2019).

271

272 *2) Do traits correspond with projected shrub range shifts and past cover change?*

273 Tundra plant species occurring in warmer climates tend to have greater height and
274 SLA (Betway, Hollister, May, & Oberbauer, 2021; Bjorkman, Myers-Smith, et al.,
275 2018), and warmer conditions are expected to expand in the near future (Pearson et
276 al., 2013). Thus, we expect that individuals occupying warmer climatic niches and
277 having more competitive strategies (greater height and SLA values) and increased
278 dispersal capacity (small seeds) will occupy larger projected ranges and have
279 undergone cover increases under a warming climate. We also hypothesise that
280 species with greater ITV in all three traits will have greater projected ranges as they
281 are likely to be adapted to a wider climatic niche in their current range, and thus
282 undergo future range expansion with warming.

283

284 *3) Which are the winner and loser shrub species in a warming tundra and what*
285 *are their trait combinations?*

286 Tall plants with wind-dispersed seeds are usually more competitive as they have
287 facilitated seed dispersal and shade shorter plants (Westoby, 1998). We expect
288 winners (those projected to expand their ranges or having increased in cover) to be
289 mainly tall shrubs, given that they are the current dominant life form in warmer niches,
290 and losers (those projected to contract their ranges) to be mostly dwarf shrubs, which
291 tend to predominate in the colder part of the climatic niche (D. A. Walker et al., 2005).
292 We hypothesise that species with greater ITV in all traits will be winners, and vice
293 versa for losers. Finally, we presume that species that have increased in cover are
294 also projected to experience range expansions with warming, following the
295 abundance-range size relationship theory (Gaston & Blackburn, 2008).

296

297 **Methods**

298 *Definitions and taxonomy*

299 The tundra is defined as the region beyond the elevational and latitudinal treeline
300 (Berdanier, 2010). We consider shrubs as multi-stemmed woody plants under 5-6 m
301 in height (Wilson, 1995). We followed the taxonomy outlined in The Plant List
302 (<http://www.theplantlist.org/>) at the species level and standardised synonyms
303 according to this reference. Definitions of the three traits follow Kattge et al., (2020)
304 which in turn follow Garnier et al., (2017).

305

306 *Trait data*

307 We extracted a total of 17,921 trait records from the TRY 5.0 (Kattge et al., 2020) and
308 the Tundra Trait Team (TTT) databases (Bjorkman, Myers-Smith, et al., 2018) for
309 three plant size and economics traits related to competitive ability and dispersal (plant

310 height, SLA and seed mass) for 62 shrub species across three continents (**Figure 1,**
311 **Table S4-S6**). From the total, three trait records were from the literature and 192
312 records were collected by the authors and unpublished thus far. We removed the
313 observations with values greater than four standard deviations from each species
314 mean following the protocol outlined in Bjorkman et al. (2018). Functional traits have
315 been correlated to each other in the literature (Dupré & Ehrlén, 2002; Moles &
316 Westoby, 2004; Pollock et al., 2012), but we did not find correlations between the traits
317 in this dataset that might have influenced our statistical outcomes (**Table S2.17-19**).
318
319 We retained all georeferenced records above 30 degrees north in latitude, as we were
320 interested in trait variation per species beyond tundra biome values. Trait data from
321 more southern latitudes could be indicative of the trait changes that tundra species
322 could experience in a warmer future due to adaptation, phenotypic plasticity or gene
323 flow (Bjorkman et al. 2018, Thomas et al. 2020). We included non-georeferenced trait
324 records from databases that we were certain contained records from high-latitude
325 ecosystems (e.g., if an approximate location/site name was provided). We retained
326 only records that reported single values and individual means. We kept control and
327 ambient values only and removed all experimental treatments and herbarium
328 specimens as we were interested in traits from unmanipulated wild specimens. For
329 each species-by-trait combination, we only retained those with more than four records,
330 providing a dataset with 62 species. We calculated 'trait values' (MTV) as the median
331 per species and 'trait variation' (ITV) as the standard deviation (SD) of all trait values
332 per species (**Figure 1**). We chose SD as a commonly used ITV metric with a more
333 conservative data distribution than others like the coefficient of variation (COV);
334 however both metrics were directly proportional (**Table S4-S6, Figure S6**). We

335 compared ITV values using a random sample of five records versus all available
336 records and found very similar data distributions, thus we opted for including all
337 available records for ITV calculation (**Table S4-S6**). We log-transformed the median
338 and SD values with the natural logarithm because the differences between species
339 are better characterised on a log-scale (Bjorkman, Myers-Smith, et al., 2018; Thomas
340 et al., 2020; Westoby, 1998).

341

342 To explore the influence of categorical traits, we obtained data on taxonomic family,
343 functional group, dispersal mode and deciduousness from a variety of sources
344 including TRY and online florae combined with expert knowledge (see 'Online sources
345 of categorical traits and maximum height' in Appendix). To group species according to
346 height, we extracted the potential maximum canopy height per species from online
347 florae (see Appendix) and assigned the species a category following the classification
348 in Myers-Smith et al. (2015): dwarf shrubs (< 20 cm), low shrubs (20 - 50 cm), and tall
349 shrubs (> 50 cm). Maximum canopy height is a relevant method to classify species
350 given our interest in the height that species could achieve in warming conditions (i.e.,
351 current height of species at sites outside the Arctic), rather than its average
352 representative height in the Arctic. We used values from online florae rather than
353 TRY/TTT values to avoid circularity in defining functional groups. This could mean that
354 online florae values (mostly from the Arctic) would reflect shorter values than TRY/TTT
355 (which include records outside the Arctic).

356

357 When screening identified duplicate records per species, trait, coordinates and
358 collector/databases, we consulted the original datasets (when available) to investigate
359 if potential duplicates were actual values. If both values (i.e., including duplicates)

360 appeared in the original dataset, they were considered valid records. We removed
361 records that were clearly duplicates ($n = 129$), either because they were found both in
362 TRY and TTT, or because the original database showed no duplicates. We identified
363 two mistakes in trait units or coordinates, which we double-checked with the original
364 data contributors and corrected accordingly.

365

366 Since we only had original seed mass data for 28 species (as opposed to 57 species
367 for SLA and 52 species for height), we gap-filled seed mass data for an additional 12
368 species that had data on both height and SLA but no seed mass data. To gap-fill, we
369 extracted data at the genus level above 60 degrees north (to ensure Arctic
370 representative records) and for which there were records for over four individuals. We
371 then calculated the log-transformed median value and the SD at the genus level and
372 included these 12 values for the gap-filled species (**Table S1**).

373

374 To account for confidence depending on the number of observations, we calculated
375 an index value per species-by-trait combination. Species with over 20 observations
376 were assigned an index value of 1 and gap-filled species or those with five
377 observations had an index value of 0.5. For species with between 6 and 19
378 observations, we calculated the index following a linear regression (see below), where
379 N_{obs} is the number of observations per species-by-trait combination:

380
$$Index = 0.33 + \left(\frac{1}{30}\right) * N_{\text{obs}}$$

381 We used this index to down-weight species with smaller numbers of records in the
382 weighted regressions explained below (Christensen 2019, Bürkner 2017). We also
383 calculated a combined index per species by averaging the individual trait indices
384 together.

385 *Range size data*

386 We used projected current range sizes to represent present-day species ranges (see
387 Appendix). To characterize projected shifts in species range size (hereafter 'range
388 shifts'), we used SDM-derived distribution data for 62 species under 24 future climatic
389 scenarios as calculated by Blach-Overgaard et al. in prep (see 'Species distribution
390 modelling' in Appendix for details). Blach-Overgaard et al. calculated a 'no dispersal',
391 a 'limited dispersal' and an 'unlimited dispersal' scenarios. A 'limited dispersal'
392 accounts for species-specific future migration rates, which were calculated using
393 species-specific dispersal capacities in a linear mixed models framework following
394 Tamme et al. (2014), and estimate how far a species can disperse using dispersal-
395 related traits including plant height and seed size in order to quantify more ecologically
396 relevant range shifts. A 'limited dispersal' scenario incorporates geographical
397 constraints, while an 'unlimited dispersal' climatic scenario (without dispersal rates)
398 means that species in one continent could spread to another, e.g., North American
399 species would have available ranges in Europe, and vice versa. Thus, 'unlimited
400 dispersal' scenarios do not consider geographical realities and would likely over-
401 estimate range sizes. We compared the three dispersal scenarios and concluded that
402 a 'limited dispersal' scenario would be the most realistic and thus chose this scenario
403 as representative of range shifts (**Figure S1**). We also determined that the potential
404 circularity on using the 'limited dispersal' scenario does not influence the main findings
405 of this study (see 'Use of traits in model projections' in Appendix, **Figure 5, Figure S2,**
406 **Table S2**).

407

408 Projected species range shifts were computed both as relative (%) and absolute (km²),
409 and 'range shifts' only reflect a change in the overall range size over time (not changes

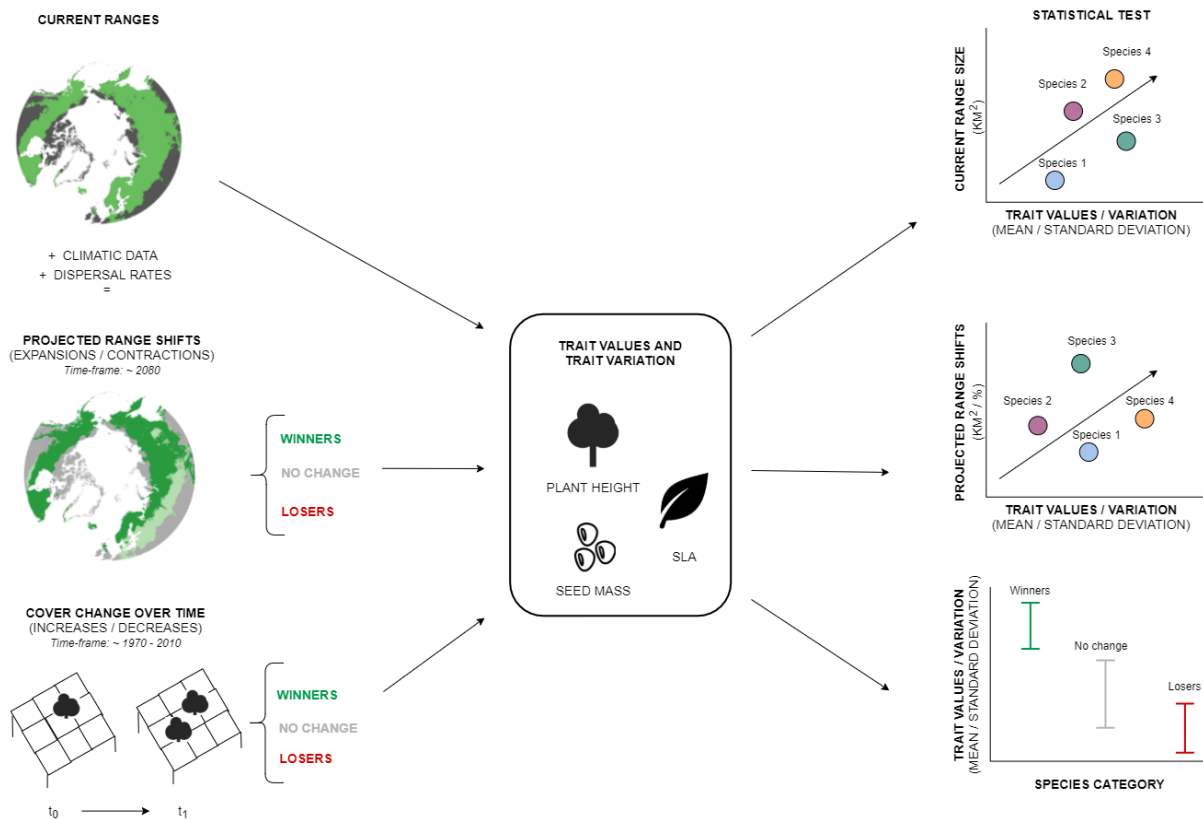
410 in the shape or location of the ranges). We refer to 'range shifts' when we include both
411 projected increases and decreases in total range size, and to 'range expansions' and
412 'range contractions' when referring to projected range size increases and decreases,
413 respectively (**Figure 1**). We log-transformed (with the natural logarithm) and centred
414 current range sizes as the values were not always normally distributed and included
415 outliers. Since the projected range shift data included negative values, we first divided
416 the absolute range changes by a million km² and the relative range changes by 100,
417 in order to bring the values closer to zero. We then added a constant value (the
418 negative minimum value plus one) so all values were positive, and afterwards log-
419 transformed these values. Finally, we centred these values on zero before carrying
420 out the statistical analysis in order to facilitate convergence (Harrison et al., 2018,
421 Bolker et al. 2013).

422

423 *Classification of winner and loser shrub species*

424 We classified winner and loser shrub species using 1) projected range shifts from the
425 SDMs (into the years 2070 – 2099) and 2) cover change over time from the
426 International Tundra Experiment (ITEX) dataset (between 1970 - 2010). For range shift
427 projections, we calculated the 25%, 50% and 75% quantiles of species' projected
428 range shifts across the 24 climatic scenarios (both for absolute and relative range
429 shifts) and categorised species as winners (if the 25% quantile was above zero), no
430 change (if any quantile overlapped zero) or losers (if the 75% quantile was below zero).
431 For cover change over time, we analysed shrub cover change over time from 105
432 subsites and 30 sites from the ITEX network (Henry and Molau 1997). Based on the
433 analysis by Bjorkman et al. (2018), individual species' relative cover change over time
434 per plot were modelled as ordinal numbers using a Poisson distribution with subsite

435 and site as random effects, aggregating after to subsite and species level. Thus, we
 436 obtained slopes of cover change per year for each species-by-site combination. We
 437 defined winner, no change and loser cover categories according to whether these
 438 slopes per species across all sites were positive or negative, and whether the 95%
 439 credible intervals overlapped zero (**Figure S3, Table S3**).



440
 441 **Figure 1.** Conceptual diagram of the different types of data used in this study and their
 442 relationships. In the current range map, green represents the current distribution of a
 443 species. In the projected range shifts map, different green shades in the map represent
 444 the difference between current and projected ranges. In the cover change over time
 445 drawing, the point-framing grid represents cover change over time. Categories of
 446 winner, no change or loser species were identified following two different methods:
 447 based on future projections of range shifts, and based on past cover change over time.
 448 Current range sizes were modelled with trait values and variation, and projected range
 449 shifts (which could be range expansions or contractions) were modelled as a function

450 of trait values and variation. Cover change over time species categories were
451 modelled with trait values and variation.

452

453 *Statistical models: Current range sizes and traits*

454 To understand whether species' ranges were associated with traits, we fitted weighted
455 linear regressions per trait of species' current range sizes as a function of MTV,
456 weighting each record according to the scoring index described above. We also
457 modelled current range size as a function of the three traits' MTV together for those
458 species which had trait data for all three traits (weighting according to the combined
459 index), and as a function of three two-way interactions of these three traits. To evaluate
460 whether range size was explained by categorical traits, we fitted separate models with
461 current range size as a function of deciduousness (evergreen/deciduous), functional
462 group (tall/low/dwarf shrub), dispersal mode (berry/wind-dispersed) and taxonomic
463 family. We modelled MTV as a function of species' range category (winner, no change,
464 loser) per trait to identify differences in trait values between the different species
465 categories. We also modelled categories as a function of all three different traits to
466 understand whether winners differed in their trait combinations from loser and no
467 change species (as this was indicated in the PCA analysis described below). To do
468 this, we fitted an additive weighted binomial model with a Bernoulli distribution by
469 assigning a value of 0 to loser and no change species, and a value of 1 to winners.
470 We do not include here the variant of that model with an interaction element since the
471 model did not converge with that level of complexity. Finally, we fitted similar weighted
472 regressions as described above, with the same structure but with ITV instead of MTV
473 **(Figure 1, Table S2).**

474

475 *Statistical models: Species range shifts and traits*

476 To understand if species' range shifts were associated with traits, we fitted weighted
477 linear regressions of relative and absolute range change as a function of MTV per trait,
478 each with the 25%, 50% and 75% quantile range change (of the 24 climatic scenarios)
479 as a response variable. We also modelled both median relative and absolute range
480 shifts as a function of all three traits (using the combined weighting index), and as a
481 function of their three two-way interactions. To evaluate whether range shifts were
482 explained by categorical traits, we fitted separate models for absolute and relative
483 range shifts as a function of deciduousness, functional group, dispersal mode and
484 family. To understand the processes of range expansion and contraction individually,
485 we fitted separate weighted regressions for species that are predicted to experience
486 range 'gains' and 'losses' (defined as those species whose median range change was
487 above and below zero, respectively, both for absolute and relative changes). We
488 modelled median range 'gains' and 'losses' as a function of trait values per individual
489 trait, and then as a full model with all three different traits, and their three two-way
490 interactions, for absolute and relative changes. We fitted similar weighted regressions
491 as described above, with the same structure but with ITV instead of MTV (**Figure 1,**
492 **Table S2**). Finally, to understand if traits were related to past cover change, we fitted
493 weighted linear regressions of the slopes of cover change over time (1970 – 2010) as
494 a function of MTV and ITV, and modelled the slopes of cover change over time as a
495 function of all three traits (**Table S2**). We also modelled cover categories (winners, no
496 change or losers) as a function of the three traits' MTV and ITV in an additive weighted
497 binomial model with a Bernoulli distribution similarly to above.

498

499

500 *Statistical models: Distribution models*

501 To understand whether species' absolute and relative ranges were related, we fitted
502 a linear model of absolute versus relative range shifts. To investigate whether species
503 with a larger current range were projected to expand more, we modelled future ranges
504 as a function of current range sizes. We also fitted weighted linear regressions of
505 current range sizes as a function of category (winner, no change or loser), and with
506 median range change (both absolute and relative) as a function of category per
507 individual trait to understand whether species' trajectories were related to smaller or
508 larger present and future ranges (**Table S2**).

509

510 *Statistical models: Ordinations and analyses of variance*

511 To identify differences between species groups, we performed two Principal
512 Component Analyses (PCAs): one for MTV and another for ITV, using the 'prcomp'
513 function in the R 'stats' package. We centred and scaled log-transformed trait values
514 prior to computing the PCA. We used the R package 'AMR' (Berends et al., 2021) to
515 visualize the trait space for the 36 species for which we had data available on all three
516 traits (including gap-filled species), and plotted the first two component axes. We
517 extracted the PCA scores per species and used them as response variables in linear
518 models against current range sizes, absolute and relative range shifts, and cover
519 change slopes, and we modelled individual PCA scores as a function of winner, loser
520 or no change range category, both for MTV and ITV, and for range and cover species
521 categories.

522

523 We performed a permutational multivariate ANOVA test (PERMANOVA) to determine
524 if the different groups (winners, no change or losers) differed statistically in trait space,

525 both for MTV and ITV. We used the ‘adonis’ function in the R package ‘vegan’
526 (Oksanen et al., 2020) and specified Euclidian distance with 999 permutations. We
527 also calculated average distance to centroids per group with the ‘betadisper’ function
528 in ‘vegan’, and performed an ANOVA test to confirm homogeneity of dispersion among
529 the groups ($p > 0.05$). When the ‘adonis’ analysis yielded a significant difference
530 between categories ($p < 0.05$), we performed pairwise comparisons between them.
531 We used the ‘pairwise.perm.manova’ function in the ‘RVAideMemoire’ package
532 (Hervé, 2020) for 999 permutations and fitted the tests of Pillai, Wilks, Hotelling-
533 Lawley, Roy and Spherical, and specified different methods for p-value adjustment,
534 including Holm and Bonferroni, and with no p-value adjustment. All tests yielded
535 similar significance results. We followed the same methods outlined above for the
536 range and the cover change categories.

537

538 *Software and model specifications*

539 We used the software and programming language R version 3.6.2 (R Core Team,
540 2020) for all analyses. We fitted all Bayesian models using the ‘brms’ package
541 (Bürkner, 2017) and ran them for as many iterations as necessary to achieve
542 convergence, which we assessed through examination of the R_{hat} term and trace plots.
543 We considered that there was a clear relationship between variables when the 95%
544 credible intervals of the estimates did not overlap with zero.

545

546 **Results**

547 Plant trait records were represented across three continents (17,921 records). SLA
548 records were recorded for the most species ($n = 5,909$ records, $n = 57$ species). Plant
549 height records were numerous ($n = 11,466$ records, $n = 52$ species) and widespread
550 geographically, while seed mass records were fewer ($n = 546$ records, $n = 28$ species
551 without and $n = 40$ species with gap-filled data; **Figure 2a, Table S4-6**). By definition,
552 there were differences in plant height values between the different functional groups,
553 with tall shrubs having greater height values than low and dwarf shrubs (**Figure 2b**).
554 In contrast, most of the seed mass median values overlapped across functional
555 groups, and the heaviest seeds belonged to dwarf shrubs (**Figure 2c**). Most median
556 SLA values also overlapped, with both the highest and the lowest median recorded for
557 low shrubs (**Figure 2d**).

558

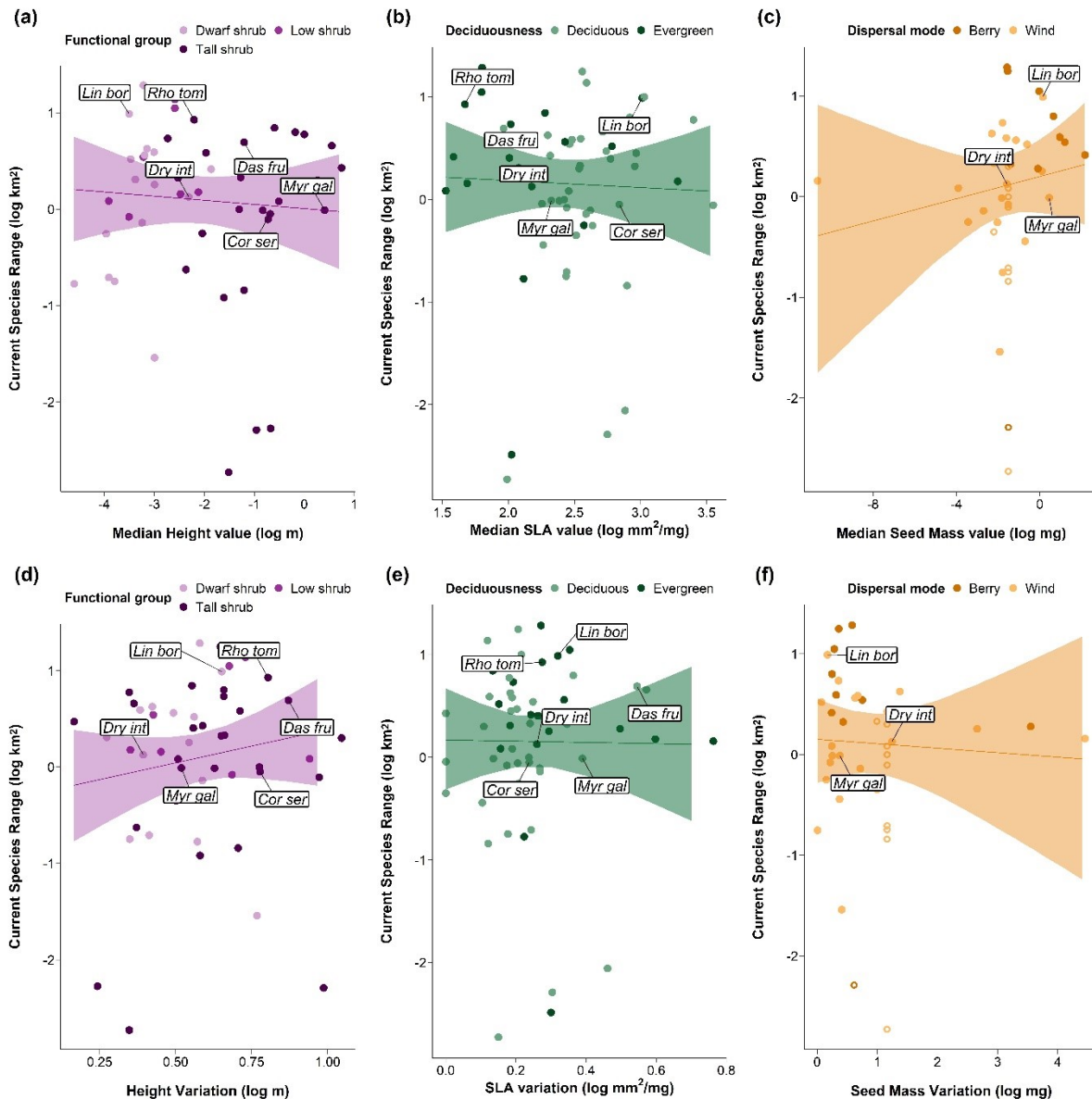
560 **Figure 2.** We compiled trait data from shrubs across three continents to test whether
561 trait values and variation were related to range size, projected range shifts and cover
562 change. Trait records with no coordinate information are not represented in the map.
563 **a)** Location of the geo-referenced trait records in this database, north of 30 degrees
564 latitude. Polar projection. **b)** Plant Height values (in m) for 52 species. **c)** Seed mass
565 values (in mg) for 40 species. **d)** SLA values (in mm²/mg) for 57 species. Each
566 coloured point represents an individual trait value recorded for that specific species.
567 Coloured points are semi-transparent, with darker colour tones indicating overlaps of
568 multiple points. Black points indicate the median value per species. Open black circles
569 indicate the median values of seed mass for gap-filled species. Species are organised
570 alphabetically within functional groups.

571

572 We did not find any clear relationships nor interactions between current range sizes
573 and MTV (**Figure 3a, b, c**), nor between current range sizes and ITV (**Figure 3d, e,**
574 **f**). There were no clear relationships between MTV or ITV and range winner, loser or
575 no change categories. There were also no differences in current range sizes
576 depending on species' dispersal mode, deciduousness, functional group or taxonomic
577 family, except for Salicaceae species having smaller ranges than the Rosaceae family
578 (**Table S2.29**).

579

580



581

582 **Figure 3.** There were no clear relationships between MTV or ITV and current range

583 sizes. Model outputs of the weighted linear regressions of current species range size

584 as a function of **a)** height values **b)** SLA values, **c)** seed mass values, **d)** height

585 variation, **e)** SLA variation and **f)** seed mass variation. MTV are the median per species

586 and ITV is the SD of trait records. Points are raw values and coloured according to

587 categorical traits related to each continuous trait. Lines are the predicted model slopes

588 and the semi-transparent ribbons represent the 95% model credible intervals. Open

589 circles in **c)** and **f)** represent the gap-filled seed mass points calculated from genus

590 medians. Labels represent abbreviated species as the top three winners
591 (*Rhododendron tomentosum* [previously *Ledum palustre*], *Dasiphora fruticosa* and
592 *Myrica gale*) and the bottom three losers (*Linnaea borealis*, *Cornus sericea* and *Dryas*
593 *integrifolia*).

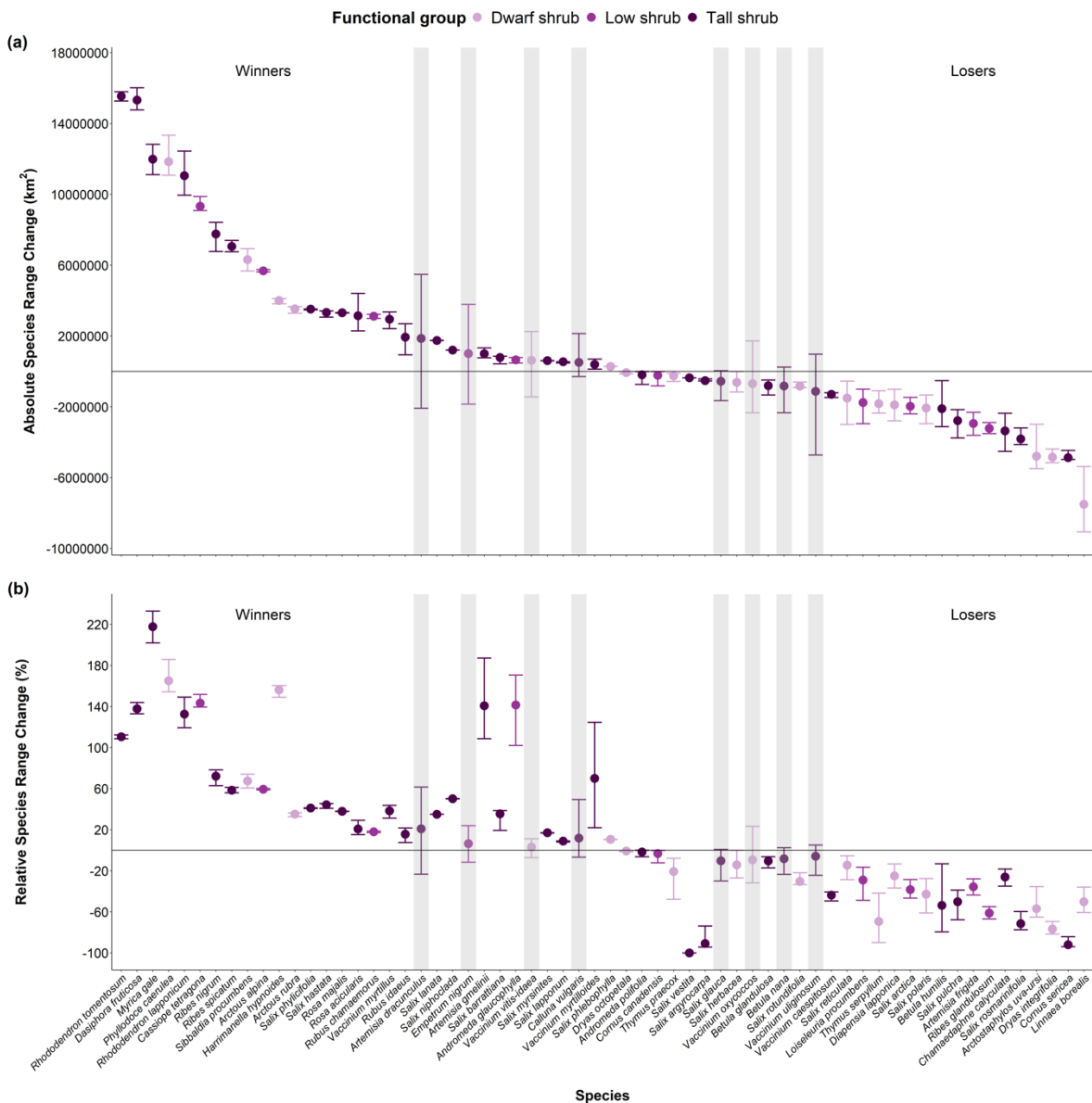
594

595 The projected range shifts method indicated similar numbers of winner ($n = 28$, 45.2%)
596 and loser shrub species ($n = 26$, 41.9%), and fewer no change species ($n = 8$, 12.9%)
597 (**Figure 4**). Among losers, 11 (42.3%) were dwarf shrubs, five were low shrubs
598 (19.2%) and 10 were tall shrubs (38.5%). As for no change species, two were dwarf
599 shrubs (25%), one was a low shrub (12.5%), and five were tall shrubs (62.5%). Among
600 winners, five were dwarf shrubs (17.9%), four were low shrubs (14.3%), and 19 were
601 tall shrubs (67.8%). The winner tall shrubs were also the category-by-functional group
602 combination with the largest number of species in this dataset. All species shared the
603 same range winner, no change or loser category whether considering absolute
604 (**Figure 4a**) or relative range shifts (**Figure 4b**).

605

606 In absolute range change terms, top winner species were the tall evergreen shrub
607 *Rhododendron tomentosum*, and the tall deciduous shrubs *Dasiphora fruticosa* and
608 *Myrica gale*. The bottom losers were the dwarf evergreen shrubs *Linnaea borealis* and
609 *Dryas integrifolia*, and the tall deciduous shrub *Cornus sericea* (**Figure 4b**). Species'
610 current range sizes and species projected range shifts were related (slope = 118.39,
611 CI = 91.73 to 143.46), and so were median absolute range shifts and median relative
612 range shifts (slope = 55,658.03, CI = 45,319.41 to 65,975.12). Cover change methods
613 identified a majority of no change species ($n = 19$, 52.7%), nine winners (25%), and
614 eight losers (22.2%) (**Table S3**). All functional groups were represented in winner, no

615 change and loser species. Only 10 species shared the same range and cover
 616 categories, with four winners, one no change and five loser species in common.



617
 618 **Figure 4.** There were similar numbers of winner and loser species on the basis of their
 619 predicted species range change in this database for projected **a)** absolute and **b)**
 620 relative range change. Each point represents the median across the 24 predicted
 621 climatic scenarios per species, while the error bars represent the 25% and 75%
 622 quantiles of range change. Species are ordered across the horizontal axis in
 623 descending absolute change median value and coloured according to their functional

624 group. Those species whose lower quantile does not overlap zero are considered
625 winners with expanding ranges, those whose either quantile overlaps zero are
626 considered to experience no change (also indicated by the vertical grey polygons),
627 and those whose upper quantile does not overlap zero are considered losers with
628 contrasting ranges. The horizontal black line represents zero range shift.

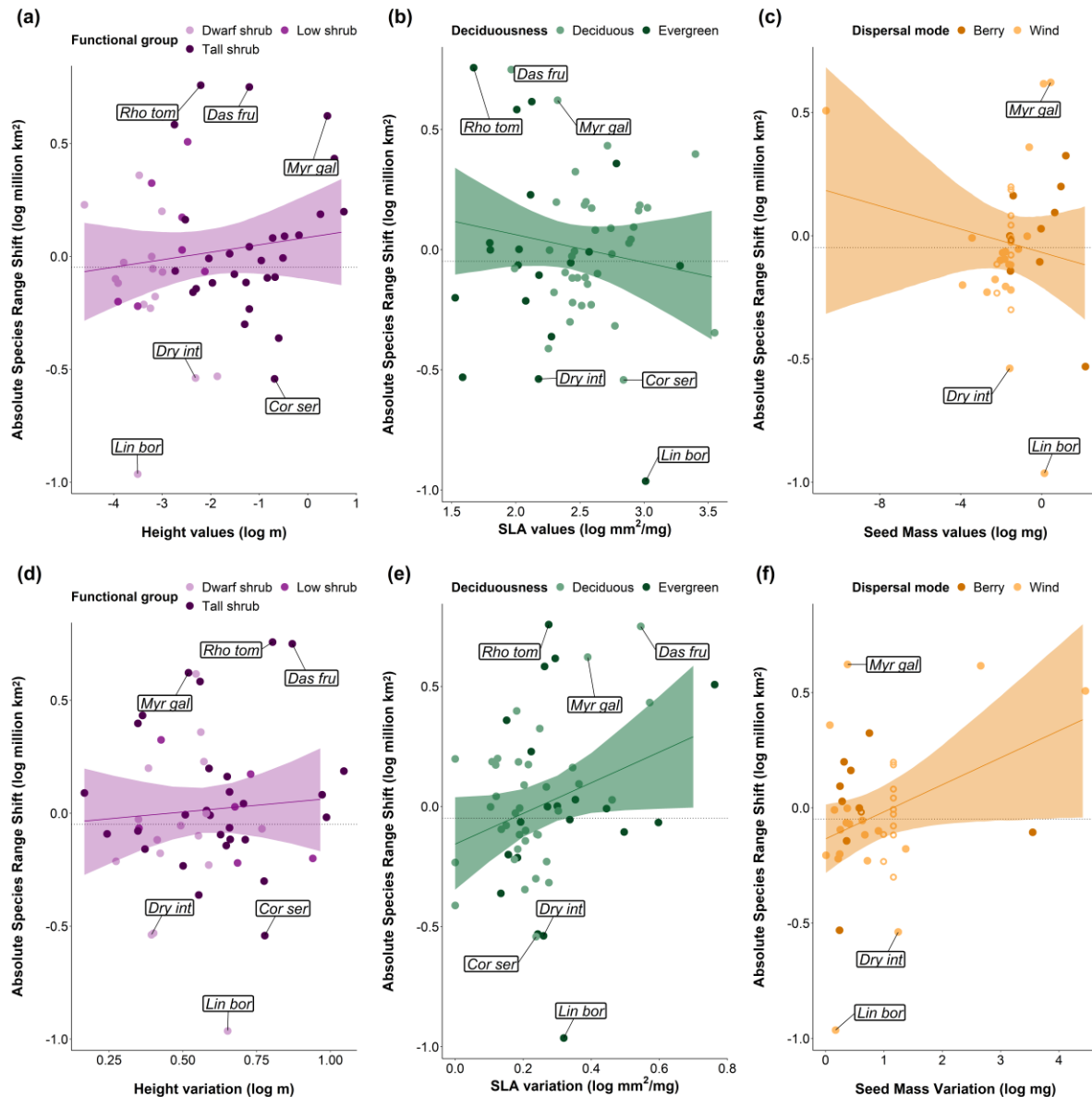
629

630 Greater seed mass values were associated with greater median absolute range losses
631 in the multivariate model (slope = -0.1, CI = -0.2 to -0.01). There was also a positive
632 interaction between height and SLA for relative median range contractions (slope =
633 0.6, CI = 0.02 to 1.17), with taller species with greater SLA having greater range
634 contractions. Shrub species with greater SLA variation had greater absolute range
635 shifts (75% quantile, slope = 0.68, CI = 0.1 to 1.25, **Figure S4a**), greater relative range
636 shifts (25%, median and 75% quantile, **Figure S4b, Table S2**), and greater relative
637 range expansions (median, slope = 0.55, CI = 0.08 to 1.03, **Figure S4c**). A 0.5
638 mm²/mg SLA variation increase was associated with 18 times greater projected
639 absolute range shifts, double the relative projected range shifts and more than double
640 the relative species expansions (**Figure S4a, b, c**). Species with greater seed mass
641 variation had greater absolute range shifts in univariate models (25%, median and
642 75% quantiles, **Figure 5f, Table S2**). This was also the case when subsetting for wind-
643 dispersed species only (slope = 0.16, CI = 0.02 to 0.29). Note that the median absolute
644 range shift model was only significant for the model including gap-filled species, but
645 not for the model without gap-filled species. Greater seed mass variation was related
646 to median relative range gains (slope = 0.11, CI = 0.01 to 0.21) and absolute range
647 gains (slope = 0.1, CI = 0.002 to 0.2). Range expansions were ~991,273 km² larger
648 for each mg of seed mass variation at lower values, with these relationships saturating

649 at higher values of seed mass (**Figure S4d**). We did not find any other relationships
650 between the different MTV (**Figure 5a, b, c**) or ITV (**Figure 5d, e**) and median species
651 range changes. We did not find any relationships between MTV or ITV and winner,
652 loser or no change category. There were also no differences in projected range shifts
653 depending on species' dispersal mode, deciduousness or functional group. However,
654 the Caprifoliaceae family had smaller range shifts than other families, and the
655 Myricaceae family had greater relative range shifts than Salicaceae. We did not find
656 any clear relationships between the slope of average cover change over time and MTV
657 or ITV (**Table S2.134-141**).

658

659



660

661 **Figure 5.** There were no clear relationships between MTV or ITV and median
 662 projected range shifts, except for seed mass variation. Model outputs of the weighted
 663 linear regressions of median absolute species range change as a function of **a)** height
 664 values **b)** SLA values, **c)** seed mass values, **d)** height variation, **e)** SLA variation, and
 665 **f)** seed mass variation. MTV represent the median per species and ITV is calculated
 666 as SD. Points are raw values and coloured according to categorical traits related to
 667 each continuous trait. Coloured lines are the predicted model slopes and the semi-
 668 transparent ribbons represent the 95% model credible intervals. Open circles in **c)** and

669 **f)** represent the gap-filled seed mass values. Labels represent abbreviated species as
670 the top three winners (*Rhododendron tomentosum*, *Dasiphora fruticosa* and *Myrica*
671 *gale*) and the bottom three losers (*Linnaea borealis*, *Cornus sericea* and *Dryas*
672 *integrifolia*). Horizontal dotted lines indicate the zero range shift after scaling the data.
673 Species above this line are winners and species below this line are losers.

674

675 In the MTV PCA of range categories, no change species were found across the
676 spectrum, losers had medium to low SLA and height values, and winners had greater
677 SLA and height values. PC1 was mainly driven by SLA and seed mass (loadings =
678 0.65 and 0.6, respectively), and PC2 was driven mostly by height (loading = -0.86).
679 PC1 explained 44% and PC2 explained 30% of the dataset variation (**Figure 6a**). We
680 did not find a significant difference between groups according to the PERMANOVA
681 analysis ($F = 0.182$). There were no significant differences between clusters according
682 to the pairwise comparisons for all tests and p-adjustment methods. We did not find a
683 relationship between range categories and trait values in our binomial model, though
684 plant height was marginally significant (**Figure 6c**).

685

686 In the ITV PCA, no change species occupied a small part of the trait space, with
687 medium to high seed mass and SLA variation, but medium to low height variation,
688 while losers occupied a larger part of the trait space. Winners occupied the largest trait
689 space for all three traits, and those species with higher variability in plant height were
690 winners. PC1 was mainly driven by seed mass and SLA (loadings = 0.68 and 0.63,
691 respectively), and PC2 was driven mostly by plant height (loadings = -0.91). PC1
692 explained 49% and PC2 explained 31% of the variation in the dataset (**Figure 6b**). We
693 did not find a significant difference among clusters in the PERMANOVA test ($F = 0.4$),

694 but winner clusters were slightly different to no change clusters (Tukey test of
695 multivariate dispersions, $p = 0.049$). Further, in our binomial model greater seed mass
696 variation was more likely to correspond to winners (slope = 1.47, CI = 0.09 to 3.27;
697 **Figure 6d**). PC2 component scores had a negative relationship with relative range
698 shifts (**Table S2.154**), but we did not find any other clear relationships when modelling
699 current range sizes, absolute range changes and relative range changes as a function
700 of PC1 and PC2 component scores, for either MTV or ITV. We did not find differences
701 either in winner, loser and no change categories for PC1 and PC2 scores, neither for
702 MTV nor ITV.

703

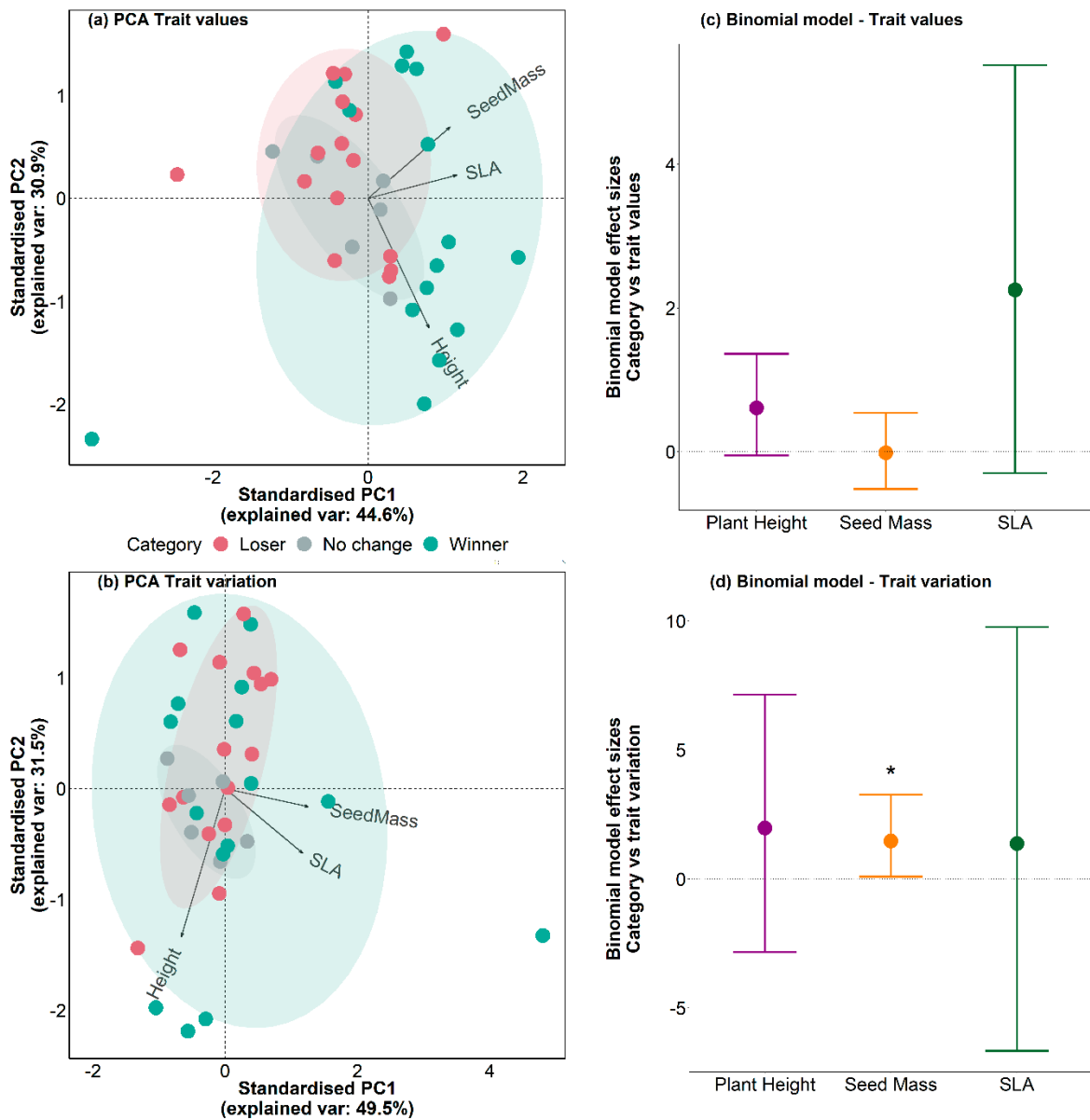
704 Species categories based on cover change overlapped largely in the MTV PCA, with
705 losers having the larger trait space (**Figure S5a**). PC1 was driven by SLA and seed
706 mass (loadings = 0.7 and 0.57, respectively), while PC2 was driven mostly by plant
707 height (loading = -0.8). PC1 explained 41% and PC2 explained 33% of the dataset
708 variation. In the ITV PCA, clusters of loser and winner species overlapped, though
709 winners had greater height variation (**Figure S5b**). PC1 was driven mostly by SLA and
710 seed mass (loadings = 0.66 and 0.65, respectively), and PC2 by plant height (loading
711 = -0.92). PC1 explained 55% and PC2 explained 29% of the dataset variation. In both
712 PCAs, we did not find a significant difference among winner, loser and no change
713 clusters in the PERMANOVA test, in the binomial models, nor when modelling mean
714 cover change over time as a function of PC1 and PC2 component scores.

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Figure 6. Range winners had slightly different trait values from loser and no change species. Principal Component Analysis for **a)** MTV and **b)** ITV ($n = 36$). Ellipses and points are coloured according to species categories. Arrows indicate direction and weighting of each trait. Ellipses indicate the 68% confidence interval of distributions per category. **c)** and **d)** Effect sizes of the binomial models with category (winners versus losers and no change) as a function of **c)** MTV and **d)** ITV. Mid-points represent mean posterior estimates and vertical error bars represent the 95% credible intervals

727 of the slope estimates. Asterisks indicate relationships between categories and traits
728 that did not overlap zero (represented by the horizontal dotted line).

729

730 **Discussion**

731 Species' range expansions/contractions and abundance increases/decreases are
732 forecasted with climate change. In this study, winner species were more likely to have
733 greater seed mass values, and greater variation in SLA and seed mass compared to
734 losers, potentially conferring an advantage in a warmer future climate. However, the
735 relationship of MTV and ITV with projected range shifts was highly dependent on the
736 range shift quantiles considered per species (**Table S2**). Contrary to our hypotheses,
737 specific values of continuous traits (e.g., shorter stature) and groups within categorical
738 traits could characterize both winner and loser species. Additionally, species projected
739 through SDMs to expand their ranges are not the same species that have increased
740 in cover over time, showing a mismatch when employing different assessment
741 methods. Species' projected range shifts may have consequences for the future trait
742 composition of tundra communities (Bjorkman, Myers-Smith, et al., 2018), but not in
743 mechanistic ways given that winners and losers share moderately similar trait spaces.

744

745 *Winners and losers in a warming Arctic*

746 Range winners tended to have greater seed mass values than no change and loser
747 species, though not in a consistent manner. Plant height, SLA and seed mass are
748 important response traits which are sensitive to climate change and thus influence
749 species' abilities of persisting in and colonise changing habitats (Baruah et al., 2017).
750 Thus, we expected tall shrubs with greater SLA to be winners due to their increased
751 competitive ability, but contrary to our expectations, heavier seeds seemed to relate

752 to range shifts more than lighter seeds. Plants with lighter seeds tend to disperse
753 further and produce more seeds (Hamilton et al., 2005; MacLean & Beissinger, 2017),
754 but larger seeds are more likely to be within berries that are dispersed by animals over
755 longer distances (Nathan et al., 2008). Moreover, large seeds are at an advantage
756 when it comes to seedling establishment due to more storage tissue (Hamilton et al.,
757 2005; Moles & Westoby, 2004), thus suggesting seed mass is not a reliable predictor
758 of range processes. Under climatologically favourable conditions, tall shrubs and those
759 with greater SLA have a competitive advantage over other species (Gaudet & Keddy,
760 1988), and the height of tundra plants has increased with warming over the past few
761 decades (Bjorkman, Myers-Smith, et al., 2018). Tall plants may expand with increasing
762 solar radiation and rainfall (Moles et al., 2009, Pollock et al., 2012,), but similar climatic
763 conditions support communities with different MTV, and different climates can support
764 communities with similar MTV (Bruehlheide et al., 2018). Therefore, while macroclimate
765 might link well with community trait values, individual trait values and ITV could instead
766 be more affected by microclimate, including factors like topography, soil moisture and
767 nutrients (Lembrechts et al., 2018; Opedal et al., 2015). While taller species represent
768 more winners than shorter species, which tended to be losers (**Figure 6a**), this climate-
769 trait mismatch could mean that tall shrubs will not necessarily take over the landscape,
770 as frequently reported in tundra projections.

771

772 Surprisingly, only 10 of the 36 shrubs (27.7%) with data on cover change over time
773 shared the same winner/loser categories as the species range categories, with four
774 winners, one no change and five loser species in common (**Figure 4, Table S2, Figure**
775 **S3**). This result does not support the generally accepted abundance-range size theory
776 (Gaston & Blackburn, 2008), but agrees with other studies (Sporbert et al., 2020). A

777 potential explanation is that the SDM-derived ranges identify potential future climatic
778 niches constrained by boundaries set by species-specific migration rates, rather than
779 the real-world climate responses of tundra shrubs. For instance, a species could be
780 classified as a winner because of an expanded climatic niche, but as a loser because
781 of decreased cover change, meaning that its fundamental niche does not track its
782 potential future climatic niche. Conversely, a species may be classified as a loser
783 because of a projected range contraction, but be able to persist *in situ* and adapt to
784 changing climatic conditions, which SDM projections would not be able to capture.

785

786 The environmental factors affecting broad geographical extents likely differ from those
787 affecting local scale abundances (Sporbert et al., 2020). Additionally, range shifts are
788 contingent on geographical context, and species responses might differ depending on
789 the space available for expansion (e.g. in North America versus Scandinavia).
790 Moreover, biotic interactions (e.g. competition, herbivory) at local scales dictate the
791 realization of potential climatic niches (Kaarlejärvi et al., 2017; Maliniemi et al., 2018).
792 Topography also influences plant growing conditions through numerous geological
793 and hydrological processes and has been shown to improve SDM predictive ability
794 (Mod et al., 2016). This complexity highlights the challenges in estimating plant
795 responses to warming where abundance increases may not translate directly into
796 range expansions derived from SDM approaches.

797

798 *Plant traits are not strongly related to species ranges or abundance*

799 While traits have been extensively linked to predicting plant success, we found that
800 the traits used in this study were weakly related to the projected range shifts and past
801 cover change of tundra shrubs (**Figure 5**). Previous studies have yielded similar

802 results: habitat availability was more relevant than selected traits as range shift
803 predictors for Swiss alpine plants (Angert et al., 2011), seed mass or plant height and
804 area were not related in herbaceous plants in Swedish forests (Dupré & Ehrlén, 2002),
805 and neither seed mass nor plant height predicted current species ranges for European
806 plants (Estrada et al., 2015). Likewise, a global meta-analysis and a systematic review
807 found no significant effect of traits (apart from habitat breadth and historic range limit)
808 on range shifts (Beissinger & Riddell, 2021; MacLean & Beissinger, 2017), and indeed
809 we found a strong positive association between current range sizes and projected
810 range shifts (**Table S2.35**). Moreover, there is some evidence of poor trait predictive
811 ability of long-term ecosystem properties, plant-environment relationships, and vital
812 rates (Kremer et al., 2014; Salguero-Gómez et al., 2018; van der Plas et al., 2020).
813 Together, these results indicate that contrary to our hypotheses and previous studies
814 (Cornwell & Ackerly, 2010; Veken et al., 2007), these three key plant traits are not
815 consistently associated with projected climate-induced range shifts.

816

817 Range shifts and cover change were also not defined by categorical traits such as
818 taxonomy, dispersal mode, deciduousness or functional group (**Table S2.126-133**).
819 We expected the *Salicaceae* or *Betulaceae* families to be the greatest winners given
820 their reported increases across tundra ecosystems (Bjorkman, Myers-Smith, et al.,
821 2018; Elmendorf et al., 2012; Myers-Smith, Forbes, et al., 2011), but our family sample
822 size was potentially too small to detect a taxonomic signal. Although wind-dispersed
823 (anemochorous) seeds generally have greater migration rates than animal-dispersed
824 (zoochorous) seeds (Holzinger et al., 2008), we did not find anemochorous species to
825 have larger current or projected ranges than zoochorous species. Thus, both wind and
826 animal dispersion might facilitate long-distance dispersal, or other factors like

827 vegetative propagation or seed viability might be more relevant in explaining dispersal
828 (Aubin et al., 2016), but the limited number of species with seed data limits our ability
829 to make broad generalisations. Deciduous shrubs have been identified as the group
830 expanding the most with tundra warming due to rapid resource acquisition thanks to
831 leaf turnover (Elmendorf et al., 2012; Prager et al., 2020), but evergreen shrubs are
832 also increasing as they seem to be more responsive to warming than originally thought
833 (Hudson et al., 2011; Vowles & Björk, 2019; Vuorinen et al., 2017), and our analyses
834 showed no range differences related to species deciduousness. All functional groups
835 are expected to be represented in a warming tundra (Chapin et al., 1996), and they
836 represent variation within traits very coarsely, with large overlaps in trait values
837 between groups (Betway, Hollister, May, & Oberbauer, 2021; Thomas et al., 2019).
838 These overlaps were thought to be due to ITV, and indeed we found an indication that
839 species with greater SLA and seed mass variation are projected to expand the most,
840 suggesting that winner species are more plastic or have greater potential to adapt to
841 changing environmental conditions due to within-population genetic variation (Bolnick
842 et al., 2011). However, these results were far from consistent and support the general
843 finding that tundra species will have highly individualistic and heterogeneous
844 responses to climate change (Bjorkman et al., 2019; Hollister et al., 2005; Myers-Smith
845 et al., 2020; Thomas et al., 2019).

846

847 *Beyond functional traits*

848 Our initial hypothesis of tundra shrubs showing similar trait responses to climate
849 change turned out to be too simplistic. This weak relationship between traits and
850 ranges might be attributable to different factors. First, the species' projected range
851 shifts might be related to traits reflecting specific dispersal and colonisation processes

852 not captured by the selected traits; thus a different suite of morpho-physiological traits
853 underpinning climatic preferences might have more explanatory power, such as leaf,
854 stem and root density, C, N and P contents, and cold hardening (Díaz et al., 2016;
855 Harrison et al., 2010; Kühn et al., 2021). Similarly, different traits might be more related
856 to local abundance than to projected range shifts. Second, there are intrinsic
857 differences in life history and physiology that are not accurately captured with these
858 particular traits or by one-time measured traits only (Hamilton et al., 2005; Volaire et
859 al., 2020). Third, SDM range projections may only quantify part of the full species
860 climatic niche due to the limitations in predictor data (e.g., uncertainties in climate
861 predictions, lack of soil temperature, moisture or nutrient data) and to potential bias in
862 the input occurrence data caused by sampling bias, biotic interactions, and long-term
863 dispersal limitations (Svenning et al., 2011). Fourth, SDM projections were constrained
864 by species-specific migration rates to avoid overestimating range shifts, but
865 uncertainties remain regarding the influence of biotic interactions on future range shifts
866 (Gough, 2006; Pearson & Dawson, 2003; Post et al., 2021; Wisz et al., 2013).
867 However, in the absence of long-term monitoring studies of traits and range shifts over
868 time, SDM-derived projections are the best spatial data currently available to test these
869 questions.

870

871 The relationships among traits and range shifts could be influenced by other factors
872 not addressed in this study. Phenology change (e.g., extended growing season length)
873 can buffer climatic impacts or alter species' survival and reproduction, for example
874 through greater temperature sensitivity in late-flowering species (Prevéy et al., 2019).
875 Future studies are needed on phenology as a trait influencing tundra plant responses
876 to climate change. Heterogeneity is expected in permafrost thawing rates and soil

877 deepening across tundra habitats, resulting in different amounts of nutrient availability
878 and consequent effects in plant trajectories (Mekonnen et al., 2018). Similarly,
879 examining the influence of microclimate, topography and edaphic conditions could be
880 an important next step to better understand distribution shifts (Hylander et al., 2015).
881 Finally, demographic processes not captured by the traits investigated in this study
882 might be determining the success of species range shifts more directly.

883

884 The filtering role of demographic processes such as survival, fecundity, germination
885 and establishment might affect range shifts more than traits per se (Hemrová et al.,
886 2017; Normand et al., 2014). Demographic processes might be more relevant than
887 dispersal in the tundra given the substantial role of microclimate in defining species
888 reproduction, but they are much harder to measure than traits (Graae et al., 2018).
889 Although long-distance colonisation is common in the Arctic, multiple successful
890 recruitment events are needed for a species to expand into a new area (Alsos et al.,
891 2007). Establishment might limit distributions more than dispersal, with establishment
892 being in turn determined by the number of viable seeds and the environment (Lenoir
893 et al., 2012). Both environmental conditions and biotic interactions such as herbivory
894 and both intra- and inter-specific competition can heavily affect demography (Ehrlén
895 et al., 2016; Gough, 2006). Further research is needed on how demography influences
896 tundra shrub distributions to understand if demographic rates could prove to be more
897 powerful predictors of climate change-induced range shifts than dispersal traits
898 (Hemrová et al., 2017; Salguero-Gómez et al., 2018).

899

900 We worked under the assumption that MTV and ITV will remain constant over time,
901 but there is an indication that plant height, leaf area and seed mass will change with

902 climate change (Bjorkman, Myers-Smith, et al., 2018; Myers-Smith, Grabowski, et al.,
903 2019). With repeated tundra trait data being rarely collected over time (Bjorkman,
904 Myers-Smith, et al., 2018), we included species records outside of the tundra to
905 account for trait plasticity and the likelihood of tundra trait values shifting in the future
906 (Thomas et al., 2020). We suggest that the collection of repeated trait data could
907 improve our understanding of individual and community trait change over time.
908 Similarly, geographical coverage in TRY/TTT across the Arctic is incomplete (**Figure**
909 **2a**) and trait data were not available for all species with distribution data (**Figure 2b,**
910 **c, d**). Species with no trait data might be precisely those which are endemic or rare,
911 and potentially experiencing range contractions, leading to an overall under-
912 representation of rare species. Further trait data collection across the Arctic would help
913 overcome the under-representation of particular traits and species, and enable the
914 replication of these analyses based on a larger number of morpho-physiological traits.
915

916 With range change data over time not yet available, SDM projections remain the only
917 current way to estimate range dynamics. Projections provide a proxy for potential
918 range shifts, and the relationships we found partly reflect the assumptions made when
919 calculating SDMs. These SDM models did not consider other environmental variables
920 beyond temperature and precipitation, and we found strong differences in projected
921 range shifts between the 24 different climatic scenarios. Once range change data over
922 time becomes available (e.g., through the GLORIA or MIREN networks), the
923 relationship between observed range shifts and traits could be further explored, and
924 SDMs can be validated against on-the-ground observations. Additionally, we chose to
925 examine ranges on the basis of traits because we were interested in the potential

926 explanatory power of traits as proxies for species distributions, but the influence of
927 projected range shifts on MTV and ITV could equally yield interesting results.

928

929 Earth system models (ESMs) assume high uncertainty (Bonan & Doney, 2018) and
930 usually simplify diverse plant communities using functional types parametrised with
931 summary trait values (Fisher et al., 2018; Wullschleger et al., 2014). However, our
932 findings suggest that plant traits poorly explain variation in tundra species distributions,
933 and that different methods result in different categories of winner and loser tundra
934 shrub species. While acknowledging that moving beyond broad functional types will
935 increase model complexity (Fisher et al., 2018), we advocate for ESMs to incorporate
936 trait variability, together with demographic processes. Progress is already underway
937 through the definition of Arctic-specific functional groups and the inclusion of certain
938 traits on Earth Land Models, improving overall projections (Sulman et al., 2021). In
939 order to more accurately project tundra vegetation shifts, incorporating the real-world
940 complexity inherent in the diverse tundra shrub responses to a warming climate
941 remains crucial.

942

943 **Conclusions**

944 Our findings indicate that no specific combination of trait values or variation is
945 associated with winner or loser tundra shrub species under climate change. Contrary
946 to our expectations, particular trait values or greater trait variation do not necessarily
947 indicate increased range or abundance shifts, although there was a broadly positive
948 signal of greater seed mass values with projected range shifts, and greater SLA and
949 seed mass variation with projected range shifts. Overall, we observed similar values
950 of height, SLA and seed mass for both range expanding and contracting tundra shrub

951 species. Thus, projected range shifts will not lead to directional shifts in shrub trait
952 composition or variation, as both winner and loser species share a relatively similar
953 trait space. Additionally, winner and loser species differ when comparing past cover
954 change over time with projected range shifts. Future research could investigate the
955 explanatory power of other morpho-physiological traits and address how demographic
956 processes might mediate tundra shrub range shifts. Our results demonstrate that
957 tundra shrubs can be equally resilient or vulnerable even with very different
958 combinations of trait values and variation. Identifying the future winners and losers of
959 climate change in the tundra biome remains a complex endeavour, but these results
960 outline that the wide variety of evolutionary strategies that tundra plants employ are
961 not necessarily reflected in their responses to a warming climate.

962

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