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10 11	AUTHORS: John Guittar ¹ , Deborah Goldberg ¹ Kari Klanderud ³ , Richard Telford ² , Vigdis						
12	Vandvik ² ,						
13							
14	¹ Ecology and Evolutionary Biology, University of Michigan						
15	² Department of Biology, University of Bergen, Bergen, Norway						
16	³ Ecology and Natural Resource Management, Norwegian University of Life Sciences, Ås,						
17	Norway						
18							
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20	1. This manuscript (<i>traits_transplants_2016-06-04.docx</i>).						
21	2. AppendixS1 (AppendixS1.docx).						
22	3. Supplementary files: The metadata file (<i>supplementary_file_metadata.docx</i>) lists and						
23	describes the supplementary files, which include the central R Markdown file used in the						
24	analysis (<i>traits_transplants.Rmd</i>), the scripts that it sources (<i>custom_functions.R</i> ,						
25	bayesian_immigration_estimates.R, neutral_simulation.R, simdat_processing_veg.R,						
26	<i>simdat_processing_traits.R, simdat_spp.R</i>), and a table of the species found in this study						
27	and their associated trait data (<i>species_data.csv</i>).						
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30 **Abstract:** Plant functional traits vary consistently along climate gradients and are therefore 31 potential predictors of plant community response to climate change. We test this space-for-time 32 assumption by combining a spatial gradient study with whole-community turf transplantation 33 along temperature and precipitation gradients in a network of twelve grassland sites in Southern 34 Norway. Using data on eight traits for 169 species and annual vegetation censuses of 235 turfs 35 over five years, we quantify trait-based responses to climate change by comparing observed 36 community dynamics in transplanted turfs to field-parameterized null model simulations. Three 37 traits related to species architecture (maximum height, number of dormant meristems, and ramet-38 ramet connection persistence) varied consistently along spatial temperature gradients and also 39 correlated to changes in species abundances in turfs transplanted to warmer climates. Two traits 40 associated with resource acquisition strategy (SLA, leaf area) increased along spatial temperature 41 gradients but did not correlate to changes in species abundances following warming. No traits 42 correlated consistently with precipitation. Our study supports the hypothesis that spatial 43 associations between plant traits and broad-scale climate variables can be predictive of 44 community response to climate change, but illustrates that not all traits with clear patterns along 45 climate gradients influence community response to an equal degree.

Keywords: Plant functional traits, clonal traits, environmental gradient analysis, turf
transplantation, grasslands, alpine plant communities, community response.

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50 INTRODUCTION

51 Plant functional traits, defined as measurable species characteristics with explicit 52 connections to individual performance, reflect plant ecological strategy and associate with 53 environmental factors at many spatial and ecological scales (Silvertown 2004, Wright et al. 2005, 54 McGill et al. 2006, Violle et al. 2007). The roles that environmental variables play in structuring 55 community composition are often inferred from patterns of community-weighted mean trait 56 values along spatial gradients (De Bello et al. 2005, Shipley et al. 2006, Kraft et al. 2008, 57 Cornwell and Ackerly 2009). The consistency and prevalence of many trait-climate correlations over space suggests they could be good predictors of community responses to climate change 58 59 (Lavorel and Garnier 2002, Enquist et al. 2015).

60 However, there are also reasons why spatial trait gradient patterns may be poor predictors of community responses to climate change. First, it is not clear if species will migrate quickly 61 62 enough to maintain their current associations to climate (Post and Pedersen 2008, Visser 2008). 63 Instead, species assemblages may be in continual flux as species respond and adapt differentially 64 to changing climate conditions (Neilson et al. 2005). Second, rapid climate change could disrupt 65 biotic interaction networks, leading to idiosyncratic species responses that are inconsistent with 66 expectations based on broad-scale trait-environment relationships (Kudo et al. 2004, Post and 67 Pedersen 2008). Third, species may respond to finer-scale changes in environmental variables 68 that cannot be predicted using climate averages (Kimball et al. 2010, Graae et al. 2012).

69 One way to directly evaluate the potential for spatial trait patterns to predict community 70 responses to climate change is to experimentally manipulate climate in situ and observe 71 community response (e.g. Hobbie and Chapin III 1998, Hudson et al. 2011). In situ approaches 72 allow for precise manipulation of the desired climate variables but suffer from several 73 drawbacks. Most notably, the arrival and establishment of immigrants adapted to the new climate 74 conditions is sharply reduced, effectively removing an important driver of community response 75 to climate change (Gottfried et al. 2012). In situ experiments may even suppress community 76 responses if propagule pressure from locally abundant species is high enough to exert mass 77 effects on the community compositions of experimental plots. In situ climate manipulations also 78 often have undesirable side effects related to their experimental methods (Aronson and McNulty 79 2009). 7

80 Here, we investigate the effects of climate change on plant communities using an 81 alternative approach: transplantation of entire, intact communities to new climates. Whole-82 community transplantation avoids the experimental artifacts of climate change manipulations, 83 while exposing the community to immigration from species adapted to the new environment. In 84 fact, transplantation lies at the other extreme of *in situ* climate manipulations: it provides a 85 scenario in which immigration of climate-adapted species is higher than would be expected in 86 communities subject to gradual environmental change. We monitored changes in the functional 87 composition of 235 control and transplanted turf communities over five years within a network 88 of twelve grassland sites in southern Norway. Our measures of functional composition rely on 89 species-level averages of four commonly measured plant traits: leaf area, maximum vegetative 90 height, seed mass, and specific leaf area (SLA), and four less commonly used traits relating to

91 clonal growth strategy: number of offspring per parent, persistence of plant-offspring connection,

92 rate of lateral spread, and bud number (i.e., the number of dormant meristems per ramet). Clonal

93 traits are often overlooked as indicators of plant performance, despite their widespread

94 prevalence and potential significance for community dynamics and ecosystem function,

95 especially in herbaceous plant biomes like grasslands, wetlands, and tundra (Zobel et al. 2010,

96 Cornelissen et al. 2014).

97 Our central goal was to test if traits with broad spatial associations to climate also drive 98 community responses to rapid climate change. To do this, we characterized baseline trait patterns 99 across temperature and precipitation gradients in our system, and then determined if these traits 100 correlated with species performance in turf communities transplanted to warmer and/or wetter 101 conditions. The fact that turf communities were open to immigration from the surrounding 102 vegetation necessitated a careful evaluation of our null expectations. Even under trait-neutral 103 dynamics, natural turnover combined with the immigration and proliferation of locally-abundant 104 species leads transplanted communities to converge compositionally with local sites over time. 105 Thus, any test for trait-mediated dynamics must measure community responses against null 106 expectations that account for stochastic replacement and immigration. We use shifts in species 107 abundances in control turfs to estimate stochastic replacement and immigration at each site, and 108 then use these estimates in model simulations to generate null expectations of turf response to 109 transplantation. Observed deviations from these null expectations are interpreted as evidence for 110 trait-mediated interactions.

111 The unusual topography of southern Norway allowed us to address an additional 112 shortcoming of most spatial gradient studies by methodologically separating temperature and 113 precipitation as potential climate drivers. Ecological studies along climate gradients often use 114 altitudinal transects that vary in both temperature and precipitation (Callaway et al. 2002, Djukic 115 et al. 2010), although not always in a consistent manner (Körner 2007). This covariation makes it 116 difficult to isolate the individual and interactive effects of temperature and precipitation and thus 117 project how vegetation will respond to novel climates. In southern Norway, a west-to-east 118 rainfall gradient interacts with a mosaic of fjords and mountain ridges to generate high climatic 119 heterogeneity over a small geographic area. We exploited this natural heterogeneity to establish a 120 "climate grid" in which temperature and precipitation vary orthogonally among the twelve field 121 sites, thereby allowing us to separate their effects and to identify potential interactions.

122 We use results from our gradient analysis, transplant experiment, and model simulations 123 to address three questions: 1) What is the relative influence of spatial variation in temperature 124 and precipitation on community trait composition? 2) Do the traits that respond to spatial climate 125 gradients also drive community temporal response to climate change? 3) What is the influence of 126 clonal traits relative to more commonly used leaf, seed, and canopy height traits in community 127 response to climate gradients and climate change? We expect short species with conservative 128 resource use strategies (low SLA, low leaf area, slow lateral spread) and/or high capacity for 129 resource integration (persistent ramet-ramet connections, more offspring per ramet, more buds 130 per ramet) to predominate in unproductive climates (the coldest and driest sites) relative to more 131 productive climates (the warmest and wettest sites). Our study is a rigorous experimental 132 evaluation of the assumption that trait patterns along climate gradients reflect, and can therefore 133 predict, how communities will respond to anthropogenic climate change.

134

135 METHODS

136 The study area is an approximately 500 km x 500 km region in southern Norway with 137 marked climatic heterogeneity (Figure 1). Twelve grassland sites were selected with one of three 138 mean summer temperatures (ca. 6.0, 9.0, and 10.5 °C) and one of four mean annual 139 precipitations (ca. 600, 1200, 1900, and 2800 mm), while other environmental variables were 140 relatively consistent (calcareous soil, southwest aspect, slope of about 20 degrees, and 141 comparable grazing and land-use history) (see Table S2 for precise climate data, and Klanderud 142 et al. 2015 for additional site details). The grasslands' short stature (usually < 0.3 m at peak 143 biomass) and shallow but thickly interwoven root and rhizome mats enabled the easy removal, 144 transport, and replanting of 'turfs' and their attached flora to different hillsides. Each 25 x 25 cm 145 turf contained tens to hundreds of individual stems, representing 10 - 40 vascular plant species, 146 with a mean canopy height of 9 ± 6 cm (1 SD). In accordance with predictions that climate 147 change will cause southern Norway to become warmer and wetter (Hanssen-Bauer et al. 2009), 148 40 turfs were transplanted to warmer sites, 45 turfs were transplanted to wetter sites, 30 turfs 149 were transplanted to warmer and wetter sites, 60 control turfs were replanted at the same site, 150 and 60 control turfs were delineated but left undisturbed. All non-local transplants were moved 151 one 'step' warmer and /or wetter in the climate grid. Turfs were transplanted between sites in 152 multiples of five; sample sizes differed by treatment because not all destination sites had cooler

153 and/or drier sites to serve as turf origins (Figure 1). For control turfs, origin and destination sites 154 are the same site. We refer to transplant destinations as 'target sites'; thus 'target controls' refers 155 to control turfs at transplant destination sites. Vascular plant turf community censuses were 156 conducted in 2009 (before transplantation), 2011, 2012, and 2013, for a total of 928 turf 157 community time points. Twelve turf community time points were discarded due to damaged 158 turfs. Percent cover of each species was estimated visually with the aid of a 5 x 5 cm grid. Total 159 percent cover was allowed to fall below or exceed 100% to account for bare patches and/or 160 overlapping species covers (mean cover in control plots across sites and years ranged from $87 \pm$ 25% to $127 \pm 30\%$). 161

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163 Trait data: We built a custom database containing values for up to eight traits for the 169 species present in our turf communities from across the climate grid. Woody seedlings and 164 165 unidentifiable individuals represented 1.1% total cover and were discarded. We used four common traits: leaf area (mm²), specific leaf area (SLA) (m² kg⁻¹), maximum potential canopy 166 167 height (m), and seed mass (mg), and four traits relating to clonal growth: number of offspring per parent per year (1 or \geq 2), persistence of plant-offspring connection (< 2 years or \geq 2 years), rate 168 of lateral spread ($\leq 1 \text{ cm year}^{-1} \text{ or } > 1 \text{ cm year}^{-1}$), and bud number, i.e., the prevalence of 169 170 aboveground and belowground dormant meristems. Leaf area and SLA were estimated using a 171 combination of field data and data from the LEDA online trait database (Kleyer et al. 2008). Our 172 field data derive from ~1200 leaves collected in the summer of 2012 for which SLA and leaf area 173 were calculated using established protocols (Cornelissen et al. 2003). We used Pearson 174 correlations to assess the extent to which LEDA species trait values matched field gathered trait values (SLA: $\rho = 0.69$; leaf area: $\rho = 0.73$). Maximum potential height data were mined from Lid 175 176 and Lid (2007). We drew seed mass data from the Seed Information Database (Royal Botanic 177 Gardens Kew 2014). All continuous trait values were log-transformed. Clonal trait data were 178 extracted from the CLO-PLA database (Klimešová and Bello 2009) and, except for bud number, 179 transformed from categorical to binary metrics to simplify statistical analysis. For bud number, 180 species were assigned a score of 0 (no buds) to 8 (dozens of buds) based on estimates from 181 Klimešová and Bello (2009). Data on individual traits represented 140 - 164 species (84% - 99% 182 of total cover). Eight species (3.9% total cover) were identifiable only to genus but treated as 183 species in downstream analyses. For these species, trait values were either measured in the field

(SLA, leaf area), estimated by taking the median trait values of locally-present congeners (seed mass, maximum height, clonal traits), or left blank. Species names and their trait values are provided as a supplementary table (*species_data.csv*). Only two of 28 pairwise comparisons of species trait values were significantly correlated (SLA and bud number, SLA and connection persistence; see Table S1); apart from these two exceptions, we consider trait responses to be statistically independent.

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191 **Community analyses:** We quantified differences in species composition using Bray-Curtis 192 dissimilarity. Community weighted means (CWMs) were used to quantify differences in 193 functional composition. We used species-level trait values in these calculations; thus, changes in 194 CWM reflect changes in species composition, not trait plasticity. A CWM is calculated by 195 averaging the values of a trait for all species in a community, weighted by their abundance (here, 196 percent cover). For lateral spread, connection persistence, and offspring per ramet, CWMs 197 reflected the proportion of the community with the higher value category (> 2 offspring per parent, ≥ 2 years connection persistence, or > 1 cm year⁻¹ lateral spread). Pre-transplant (2009) 198 199 turf CWMs were regressed onto temperature and precipitation site means to assess community 200 trait patterns in environmental space. AIC values were used to determine when temperature, 201 precipitation, and/or their interaction were significant predictors (p < 0.05) in abundance-202 weighted multiple linear regressions. For a deeper investigation of species-level variation in 203 community composition see Klanderud et al. (2015).

204 We quantified community change as shifts in dissimilarity over time between a turf and 205 its target site controls. Each site had five undisturbed controls and five controls replanted nearby 206 which enabled us to test for the effects of transplantation *per se*. Dissimilarity in species 207 composition among undisturbed controls was only statistically different (p < 0.05) from the 208 mean dissimilarity between undisturbed and replanted controls in 5 of 48 of turf community time 209 points, suggesting that transplantation *per se* did not noticeably affect species composition. Thus, 210 in some analyses, replanted controls and undisturbed controls are combined to increase the 211 control group sample size to ten per site.

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Null model rationale and process: We used simulations to generate null expectations of turf
 community responses to transplantation, and then determined when observed community

215 responses deviated from these null expectations. Our model is similar in principle to stochastic 216 models of species abundances using Hubbell's (2001) neutral local community model, but is 217 applied to a smaller spatial scale. For each step in the model, an individual is randomly removed 218 from the turf community and either replaced with a randomly selected offspring from the same 219 turf community (with probability 1 - m), or replaced with a randomly selected offspring from the 220 site-level community (with probability m). Each step is a 'replacement event.' The site-level 221 community is conceptually equivalent to Hubbell's 'metacommunity', and is defined as the net 222 composition of the ten control turfs present at each site. The model has two parameters: 223 replacement rate (d), the number of replacement events that occur between consecutive years, 224 and immigration rate (m), the probability that replacements are drawn from the site-level 225 community pool as opposed to from within the turf-level community pool (see next section for 226 parameter estimation). Even though turfs are only 25 x 25 cm in size, we expected within-turf 227 recruitment to be high because most species in our system exhibit some degree of clonal growth 228 (Klimešová and Bello 2009), and nearly all new stems are vegetative outgrowths from extant 229 genets rather than seed germination events (Berge, Klanderud, Vandvik, unpublished data).

230 Our model differs from Hubbell's community model in three important ways. First, rather 231 than using births and deaths of individuals to quantify demographic changes, which would be 232 impractical to measure in our predominantly clonal system, we use increases and decreases in 233 percent cover units. Second, we relax the assumption of zero-sum replacement and instead force 234 simulated percent cover to match observed percent cover in each year of the experiment. Third, 235 we allow site-level communities, i.e., the source pools for migrants entering experimental turfs, 236 to vary by recalculating them after each census. The latter two modifications account for 237 temporal variability in the productivity or composition of site-level communities due to drift or 238 short-term climatic variability.

We simulated community dynamics from 2009 to 2013 on an individual turf basis,
calculating species and trait dissimilarities to target site controls each year. Compositional
changes in each turf were simulated 100 times and the resulting values were averaged.
Simulation data for 2010 were not presented because field observations do not exist for that year.
Paired t-tests were used to determine when observed and simulated null expectations differed
significantly.

246 **Estimating model parameters:** We used community census data from our control turfs to 247 estimate replacement rate (d) and immigration rate (m) at each site. We set d equal to half the 248 sum of differences in species covers in control turfs between years at each site. We divided by 249 two because each replacement event constitutes two shifts in species covers, one increase and 250 one decrease. Values of d ranged from 19.7 to 37.4. Our method of estimating d ignores self-251 replacement and thus likely underestimates actual replacement rates; however, a visual 252 inspection of model fit under a broad range of parameter values illustrates that our results are 253 robust to moderate increases in replacement rate (Figure S3). Furthermore, it should be noted 254 that any potential underestimates in replacement rates do not affect estimates of immigration 255 rates.

We estimated *m* using a Bayesian approach based on shifts in species abundances in the five replanted control turfs at each site over three consecutive years (2011-2013), assuming neutral dynamics. The net composition of the five undisturbed control turfs at each site was used as the site-level community. The expected cover λ of species *i* in a turf community at time *t* is formally defined as

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$$\lambda_{i,t} = J_{t-1}[(1-m) \times C_{i,t-1} + m \times P_{i,t-1}]$$

where J_{i-1} is the total cover of the turf community in the previous year, $C_{i,t-1}$ is the relative abundance of species *i* in the turf community the previous year, $P_{i,t-1}$ is the relative abundance of the species in the site-level community at time *t*, and *m* is the immigration parameter. The percent cover *y*, rounded to the nearest whole number, of species *i* in turf community at time *t* was modelled assuming

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$y_{i,t} \sim \text{Poisson}(\lambda_{i,t}).$

268 We gave *m* a uniform prior with a range from 0 to 1. We also explored using an informed prior 269 (m < 0.5) based on the expected predominance of clonal growth and within-turf recruitment, but 270 this led to identical results and was dropped. We fit the model using MCMC implemented in 271 JAGS 3.4.0 (Plummer 2003). We ran JAGS through the R package R2jags (Su and Yajima 272 2012). For each model fit, we ran three chains, used a burn-in of 1000 iterations, and chose 273 initial values in different regions of parameter space. We confirmed model convergence using 274 Gelman-Rubin diagnostics (Brooks and Gelman 1998). We assessed overall model fit by regressing mean posterior estimates for percent cover on observed data ($R^2 = 0.63$). See Table S2 275

for parameter estimates. For a deeper exploration of how a Bayesian approach can be used to fita trait-neutral model of community change to time series data see Mutshinda et al. (2008).

278

279 RESULTS

280 Community weighted means (CWMs) of leaf area, SLA, maximum height and lateral 281 spread increased with temperature along spatial gradients, and CWM values of bud number and 282 connection persistence decreased with temperature along spatial gradients (Table 1, Figure 2). In 283 three of the eight traits, the best-fit weighted multiple linear regression model included 284 precipitation as a predictor variable, but the coefficient of the precipitation variable itself was 285 never significantly different from 0. The interaction of temperature and precipitation had a 286 significant effect on SLA. Exponential curves with increasing temperature fit bud number and 287 connection persistence patterns better than linear ones, reflecting stronger responses in the colder 288 part of the climate grid (Figure 2). Based on these associations, we limited our analysis of trait 289 convergence in transplanted turfs over time to the six traits with spatial associations to 290 temperature, and to turfs transplanted to warmer climates.

291 Species and trait compositions of transplanted turfs converged towards target site controls 292 over time, with the magnitude of convergence increasing with initial dissimilarity (Figure 3). 293 Rates of convergence in species composition only exceeded null model predictions that 294 accounted for random replacement by local immigrants in 2011 (Figure 4). In contrast, rates of 295 convergence in maximum height, bud number, and connection persistence consistently exceeded 296 null model predictions (Figure 4). These deviations from null expectations were driven by 297 responses across many species rather than responses in just a few of the most abundant taxa 298 (Figure S4). Site-level climate data confirm that transplanted turfs experienced consistently 299 warmer temperatures as intended (Figure S1, Figure S2).

300

301 DISCUSSION

302 Our study uses observational and experimental data to test the assumption that traits with 303 broad-scale associations to climate in space are predictive of plant community response to 304 climate change in time. This space-for-time assumption is supported when using three traits 305 related to species architecture, but not supported when using three traits related to species 306 resource use strategy. Our results underscore the importance of using ecologically relevant traits when making predictions of community response, and suggest that in our grassland system,
architectural traits may exert more influence on initial species response to rapid warming than
the more commonly used growth-related traits.

310

311 **Trait patterns along climate gradients:** Despite the large range in both mean summer 312 temperature and annual precipitation across sites, CWMs trended only with temperature. The lack of functional turnover over a nearly 2500 mm year⁻¹ increase in precipitation is surprising 313 314 given the consistent directional turnover in species composition along both temperature and precipitation gradients in our system (Klanderud et al. 2015), underscoring the fact that species 315 316 turnover does not always beget functional turnover (Hooper et al. 2002). This finding contrasts 317 with vegetation trait patterns found elsewhere over narrower ranges of precipitation (Fonseca et 318 al. 2000, Wright et al. 2005). A lack of precipitation effects could occur if soil moisture is similar 319 at all sites and/or not limiting at any sites, however this seems unlikely given the large range in 320 mean annual precipitation and the otherwise similar site abiotic conditions. Regardless of the 321 mechanism, the implication is that functional shifts in these grasslands are likely to occur in 322 response to changes in temperature, not precipitation.

323 The consistent shifts in CWMs with increasing temperature in our system signify shifts in 324 plant ecological strategy. Increases in leaf area, SLA, and the rate of lateral spread with 325 temperature suggest a shift from slow-growing stress-tolerant species to fast-growing species 326 with acquisitive resource use strategies (Sterck et al. 2006, Rusch et al. 2011). Also increasing 327 with temperature are maximum height, duration of connection persistence, and bud number, 328 three traits related to plant architecture. The increase in CWMs of maximum height may reflect a 329 tradeoff in the ability to compete for light at warm sites amenable to growth and the ability to 330 tolerate wind stress and freezing temperatures at the coldest sites (Westoby 1998, Falster and 331 Westoby 2003). Higher CWMs of bud number and connection persistence at the coldest sites 332 may reflect an increased importance of resource integration and/or recovery from disturbances 333 (Klimešová and Klimes 2007), although we see no obvious reasons why resources would be 334 patchier and/or disturbances more common at the coldest sites. More work is needed to confirm 335 the functional roles of these understudied clonal traits and their role in organizing grassland 336 species along gradients.

338 **Community responses to warming:** The central goal of this study was to test the hypothesis 339 that trait-climate relationships over space are predictive of temporal community response to 340 climate change in time, a common assumption in climate change research. Of the six traits with 341 significant trends with temperature in space, maximum height, bud number, and connection 342 persistence - three traits related to species architecture - associated consistently with turf 343 community response to warming in time. The large deviation in maximum height from neutral 344 expectations may be have resulted from competition for light being more intense in more 345 productive, warmer conditions, and taller species preempting access to light, shading out 346 competitors, and earning disproportionate returns due to size-asymmetric competition 347 (Schwinning and Weiner 1998). Species with fewer buds and reduced connection persistence 348 succeeded disproportionately following warming, suggesting that the development and 349 maintenance of these clonal traits, which are believed to support new ramets under stressful 350 conditions (Klimešová and Klimes 2007), comes at a cost when conditions are more amenable to 351 growth. That CWMs of architectural traits deviated from neutral expectations of community 352 response while CWMs of growth-related traits (SLA, leaf area, lateral spread) did not, despite 353 showing strong trends along spatial temperature gradients, is unexpected and interesting. 354 Perhaps, the capacity for rapid growth is not useful to new ramets vying for resources in 355 grassland communities already packed with established individuals (but see: Wildová et al. 356 2007). Alternatively, SLA and leaf area may be poor predictors of growth in herbaceous species 357 with photosynthetic stems. The strong responses of clonal traits to changes in temperature 358 highlight the need for more emphasis on clonal traits in studies of community response to 359 climate change and herbaceous community assembly in general.

360 Defining null expectations was challenging given the lack of standard practices of how to 361 model demographic stochasticity in predominantly clonal systems (Eriksson 1994). 362 Traditionally, demographic analyses rely on population numbers and vital rates, but the concepts 363 of individuals, populations, births, and deaths break down in clonal, modular organisms. For 364 instance, ramet number is impractical to measure and may not be demographically meaningful 365 for graminoids that form hummocks with clumps of stems (e.g. Festuca ovina), nor is it possible 366 to distinguish individuals in forbs with sprawling aboveground stems with adventitious roots 367 (e.g. Veronica biflora), or species that divide via root splitting which results in fragmentation just 368 below the litter layer (e.g. Cerastium alpinum). Our decision to simulate demographic changes

using percent cover units therefore has both practical and conceptual appeal. The drawback,
however, is that percent cover is sensitive to factors that are not demographically significant,
such as variation in phenological stage among individuals, species, and sampling times, and thus
may inaccurately reflect shifts in abundance between years. Nevertheless, our approach accounts
for demographic stochasticity, annual variation in community-level composition, and the realities
of dispersal limitation in a predominantly clonal system to generate explicit null expectations of
community response to perturbation.

376

377 Conclusions and future directions: Using patterns in CWMs along environmental gradients to 378 forecast community response to climate change is an intuitively appealing approach. Our study 379 provides qualified support for such an approach: three of the six traits with spatial associations to 380 temperature in our system associated significantly with species success following transplantation 381 to warmer climates. Evidently, spatial associations between plant traits and broad-scale climate 382 variables can be predictive of community response to climate change, but are not always so.

383 Our results shed some light on how our system could respond to climate change in the 384 coming decades. Despite high rates of annual turnover, without gaps created by disturbances, 385 virtually all replacement stems are clonal outgrowths of extant genets rather than new seedlings 386 (Bullock et al. 1995; Berge, Klanderud, Vandvik, unpublished data). Thus, the potential for 387 community change is largely limited by the prevalence of gaps and the proportion of species in 388 the seed rain that are immigrants rather than local species. Once established, warmer-adapted 389 immigrants will likely proliferate vegetatively, outcompeting species adapted to cooler 390 temperatures (Olsen et al. 2016). Our approach and conclusions underscore the importance of 391 accounting for stochasticity and immigration when making predictions of community response 392 (Tilman 2004, Shipley et al. 2011). Future studies should consider the effects of dispersal 393 limitation on short-term transient responses, and how disturbances and dispersal limitation will 394 affect long-term equilibrium responses. Predictions of 'extinction debts' and 'immigration 395 credits' in the field of habitat distribution modeling are an important step in the right direction 396 (Dirnböck and Dullinger 2004), but could be developed further by considering how and when 397 traits modulate species interactions.

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- 403

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Trait	Variable	Estimate	SE	t-statistic	p-value
Bud Number	exp(-Temp)	118.15	52.83	2.24	0.049
Lat. Spread	Temp	0.04	0.01	2.50	0.031
Leaf Area	Temp	0.05	0.01	3.83	0.004
C	Precip	< 0.01	< 0.01	-1.50	0.167
Max. Height	Temp	0.05	0.01	4.26	0.002
Offspring	(none)				
Persistence	exp(-Temp)	109.14	19.28	5.66	< 0.001
Seed Mass	(none)				
SLA	Temp	0.02	0.00	5.35	< 0.001
C	Precip	< 0.01	< 0.01	-1.24	0.251
\rightarrow	Temp x Precip	< 0.01	< 0.01	2.48	0.038

532 TABLE 1: Summary statistics for best-fit weighted linear models for each trait

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Summary statistics for best-fit weighted multiple linear regression models for each trait using mean summer temperature, annual precipitation, and their interaction as potential predictor variables, weighted by the sample size at each site (N ranges from 10 to 25). Model fit was determined using AIC values. For bud number and connection persistence, exponentially transforming the temperature axis resulted in better model fit. Turf-level community weighted trait means and significant regressions are shown in Figure 2.

541 Figure 1: Panel A: a schematic illustration of the orthogonal nature of climate variables across 542 experimental sites, with black arrows representing the directions of turf transplants in replicates 543 of five. Panels B and C show the geographical locations of experimental sites in southern 544 Norway. Symbol shapes and shadings reflect mean summer temperature levels and mean annual 545 precipitation levels, respectively, in accordance with panel A.

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547 Figure 2: Community weighted trait means (CWMs) of turfs before transplantation along natural 548 gradients of mean summer temperature (left) and mean annual precipitation (right). CWMs are 549 aggregated by site (N ranges from 10 to 25). Vertical lines show ± 1 S.D. Symbol shapes and 550 shadings reflect temperature and precipitation levels, respectively, in accordance with Figure 1A. 551 Best-fit lines are shown as solid lines when trait-gradient relationships are significant; for 552 simplicity, trend lines represent univariate regressions, even if multivariate regressions led to 553 higher AIC values. The interactive effects of temperature and precipitation on SLA is shown 554 using three trend lines (~3°C: dotted, ~6°C: dashed, ~9°C: dot-dashed). CWMs in seed mass and 555 offspring per ramet did not exhibit significant trends along temperature or precipitation gradients 556 and are therefore omitted. See Table 1 for model summary statistics.

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558 Figure 3: Changes in dissimilarity of turfs transplanted to warmer climates and target site 559 controls from 2009 to 2013. The x-axis shows Bray-Curtis dissimilarity between turfs and the 560 centroids of their control turfs in 2009; the y-axis shows how that dissimilarity changed by 2013. 561 Each symbol represents a turf community. Grev crosses represent control turfs; black circles 562 represent transplanted turfs. Dissimilarity was calculated using Bray-Curtis distance for species 563 composition (top left panel) or Euclidian distance of community weighted means (all remaining 564 panels). Symbols below zero on the y-axis reflect turf communities that converged 565 compositionally towards target controls, whereas communities above zero on the y-axis diverged compositionally. Dashed vertical lines are placed at 50% of mean dissimilarity among controls as 566 567 an approximation of natural community stochasticity. Grey ellipses represent 95% confidence 568 intervals of the centroids of control turf dissimilarities.

- 570Figure 4: Mean trait dissimilarities of transplanted turf communities and target controls from5712009 to 2013. Solid lines represent observed field data. Dashed lines represent simulated null572expectations based on the means of 100 null model simulation runs. Dotted lines represent mean573dissimilarity among control turfs within sites. Null model simulations use estimates of574replacement and immigration rates derived from our field data (see Methods). Error bars show57595% confidence intervals. Statistical differences between observed and simulated community576weighted means are shown when p < 0.05 (*).
- 577 FIGURE 1







