

1 **Projected climate change scenarios spatially decouple desert EFN-ant mutualisms.**

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5 **Abstract**

6 **Aim:** Climate change is changing species distributions globally, but predicting these impacts on
7 assemblages and their spatial overlaps under future scenarios is an ongoing challenge. Here, we
8 explore how climate change influences distributions among two mutualistic assemblages.

9 **Location:** The Mojave and Colorado Deserts, California, United States

10 **Methods:** We developed stacked species distribution models for the community of extrafloral
11 nectar (EFN)-bearing plants and their mutualistic ant community and projected these models
12 under two future climate scenarios. To assess the vulnerability of this mutualism due to spatial
13 mismatches, we examined potential shifts in geographic overlap between the EFN-bearing plants
14 and ant species under both scenarios. We analyzed the bioclimatic factors influencing species
15 richness and distribution in both the plant and ant communities, as well as their responses to
16 future climate change. We also tested whether environmental breadth and phylogeny could
17 predict the responses of ants to climate change. Lastly, we evaluated the significance of the EFN
18 community on ant species distributions by determining whether the inclusion of EFN plants in
19 ant distribution models enhances their predictive accuracy.

20 **Results:** The species richness of both the EFN-bearing plant communities and ant communities
21 decreased under both predicted climate change scenarios. The geographic overlap between EFN
22 plants and ants significantly decreased under both future scenarios. The response of different ant
23 species to climate change varied based on their environmental generalization but not their
24 evolutionary relationships. Including the EFN plant community as a predictor in the species
25 distribution models for ants improved their predictive performance.

26 **Main conclusions:** The EFN plant community is an important driver of their ant mutualists'
27 geographic distribution and diversity. More environmentally generalized ant species benefit from
28 the changing climate, whereas the EFN-bearing plants are uniformly and negatively impacted
29 despite their environmental generalization. Despite the range increase of some ant species across

30 the Mojave and Colorado Deserts, these mutualisms are vulnerable to climate change because of
31 the decrease in geographic overlap between pairs of ant and EFN-bearing plant species.

32

33 **Introduction**

34 Climate change is profoundly changing the diversity and distribution of species globally. The
35 responses of individual species to a changing climate can decrease or increase their range size, as
36 well as causing spatial shifts leading to changes in the spatial overlap of species (Thomas 2010,
37 Lenoir and Svenning 2015). Spatial overlaps play a key role in biotic interactions, and thus,
38 climate change impacts the capacity for interactions in addition to the species themselves
39 (Walther 2010, Gómez-Ruiz and Lacher 2019). The loss of the interaction partners resulting
40 from the spatial reorganization of communities can decrease the delivery of ecosystem services,
41 as well as reducing ecosystem functioning and stability (Walther 2010, Pyke et al. 2016).

42 Generalized mutualisms i.e., species have flexible interactions with multiple partners, are
43 expected to be more resilient to climate change than specialized mutualisms i.e., species rely on
44 specific partners for interactions, because having flexibility in interaction partners buffers the
45 interaction to species loss (Toby Kiers et al. 2010). However, generalized mutualisms can also be
46 vulnerable if one community spatially shifts much more than the other, leading to potential
47 declines in both participant species and the ecosystem services that they respectively provide.

48 Many recent biogeographic studies look at future changes in species distributions and
49 biodiversity (e.g., Tovar et al. 2022, Biber et al. 2023); however, relatively few of these examine
50 interacting mutualistic communities on different trophic levels (but see Vasconcelos et al. 2017,
51 Morales-Linares et al. 2021, Adedoja et al. 2024). Anticipating the impacts of climate change on
52 spatial overlaps at the community level is a necessary step for predicting and mitigating the
53 consequences of these shifts for mutualism.

54 Ant-plant interactions are a model for understanding the ecology and evolution of generalized
55 mutualisms (Heil and McKey 2003). These include ant defense mutualisms; ants obtain a
56 nutrient-rich food nectar secreted from extrafloral nectaries (EFNs) by plants in exchange for
57 defending the plant from herbivores, improving plant fitness (Heil and McKey 2003, Rico-Gray
58 and Oliveira 2007, Rosumek et al. 2009). EFNs have been reported in 3941 species of plants
59 within 108 families and have arisen 457 times independently, indicating that this trait is adaptive

60 in a wide range of systems (Weber and Keeler 2013). Global biogeographic studies have
61 documented many positive correlations between ant diversity and EFN plant diversity and that
62 they are also often mediated by climate (Luo et al. 2023). Ant-EFN interactions may be
63 fundamental to the persistence of plants in arid ecosystems because the effectiveness of ant
64 defense mutualisms for plants increases with decreasing precipitation (Leal and Peixoto 2017).
65 However, ants and plants are different physiologically and likely have different climate niches
66 and, therefore, different responses to climate change. The extent of this variation in climate
67 sensitivity and, consequently, the future capacity of this mutualism is untested. Therefore,
68 understanding how ant and plant distributions will shift is critical research to understanding the
69 vulnerability of these interactions in the face of a dramatically changing climate.

70 Species distribution models (SDMs) are powerful tools for predicting species distribution shifts
71 under a changing climate. By linking aspects of species biology, such as phylogeny and
72 environmental breadth, to predicted distribution shifts, we can gain generalizable insights into
73 how communities will respond to climate change. Understanding and predicting assemblage-
74 level responses to climate change have been proposed as critical components of ecological
75 forecasting, yet these remain challenging tasks due to incomplete field sampling of assemblages
76 (Suding et al. 2008, Walther 2010, Urban et al. 2016). One solution is to use stacked species
77 distribution models (*s*-SDMs), which extend the functionality of SDMs from understanding the
78 distribution of single species to understanding the distribution of communities (Del Toro et al.
79 2019). When stacked, the models can provide both species richness and composition for a given
80 area (Dubuis et al. 2011). *S*-SDMs stacked using probabilities provide richness estimates
81 comparable to macroecological models (MEMs), i.e., models that statistically relate species
82 richness to environmental variables, while avoiding the issues of overestimation associated with
83 thresholded *s*-SDM (Gould 2000, Dubuis et al. 2011). An advantage of *s*-SDMs is that they can
84 be developed using presence-only data, allowing researchers to leverage public biodiversity data
85 clearinghouses such as the Global Biodiversity Information Facility (GBIF) (GBIF 2022). With
86 climate change occurring now and limited time to study each community in the field, these tools
87 can provide valuable support.

88 Here, we conduct a synthesis to explore the role of current and future climate on the geographic
89 distribution of two mutualistic guilds. We tested the hypothesis that EFN mutualisms couple

90 plant and ant communities together in space but become decoupled with climate change. We
91 modelled the distributions of the EFN-bearing plant and their mutualistic ant communities of the
92 Mojave Desert and Colorado Deserts using s-SDMs. We tested for shifts in geographic overlap
93 between EFN-bearing plant and ant species under two different future scenarios to evaluate the
94 impacts on the potential for this mutualism to occur. We contrasted the environmental drivers of
95 species richness and distributions between the plant and ant communities, and their responses to
96 future climate change. We then tested if environmental breadth and phylogeny predict individual
97 ant species' responses. Finally, we evaluated evidence for the importance of EFN plants on the
98 distribution of mutualistic ants by testing the following predictions: 1) Including the EFN plant
99 community into the SDMs for ant species will improve the ant model's predictive accuracy; 2)
100 Variation in the EFN plant community richness explains variation in ant richness independent of
101 covariation that arises from shared climate needs. This synthesis contributes to our understanding
102 of the biotic drivers of species distributions, as well as the drivers of diversity and the
103 consequences of climate change for two important Mojave Desert communities.

104 **Methods**

105 *Species data collection*

106 A species list of EFN-bearing plants of the Mojave and Colorado deserts was created from the
107 paper by Pemberton (1988) that documented the percent ground cover of EFN-bearing plants
108 using field surveys. A more exhaustive list of all EFN-bearing species of the area has not been
109 published and the surveys covered the major plant communities of the area (Pemberton 1988).
110 Additionally, these EFN-bearing species have been reported to be used by ants within the
111 Mojave, Colorado or Sonoran deserts (Pemberton 1988, Chamberlain and Holland 2009). Ant
112 defense improves at least two of the included plant species' fitness: *Cylindropuntia echinocarpa*
113 and *C. acanthocarpa* (Braun and Lortie, unpub, Pickett and Clark 1979).

114 We created a list of ant species found within the Mojave and Colorado deserts that use EFN
115 nectar, honeydew or have been reported to interact with EFN-bearing plants from published
116 species lists. We used the Mojave National Preserve ant species list (Ikeda and des Lauriers
117 2008) and ant species from a published Sonoran ant-EFN interaction network (Chamberlain and
118 Holland 2009) that are also found within the Mojave desert.

119 The boundaries of the Mojave and Colorado deserts were defined as the watershed boundary
120 delineated by the USGS (USGS 2006, Figure 1). We used the minimum convex polygon (MCP)
121 around the watershed boundary map as the study boundary for extracting occurrences to increase
122 the sample size for several ant species with low sample sizes (Figure 1). We used species
123 occurrences and environmental data from within the MCP to include within the species
124 distribution models but clipped out model outputs to the study area boundary.

125 Occurrences for plant and ant species were extracted from the Global Biodiversity Information
126 Facility database (GBIF, www.gbif.org) using the `rgbif` package (Chamberlain et al. 2022). We
127 supplemented the GBIF occurrences with occurrences extracted from the Global Ants
128 Biodiversity Informatics databased (GABI) (Guenard et al. 2017). We retained species with at
129 least 10 occurrences within the MCP area as focal species, for a total of 11 EFN-bearing plant
130 species (Table 1) and 16 ant species (Table 2).

131 *Environmental variables*

132 We used 19 bioclimatic variables from WorldClim Version 2 global climate gridded data at a
133 resolution of 30 seconds ($\sim 1 \text{ km}^2$) (Fick and Hijmans 2017). The bioclimatic variables represent
134 climate averages for the years 1970-2000. We used PCA for dimension reduction to eliminate
135 correlations between the variables objectively (Harrell 2001, Dormann et al. 2013). The PCA
136 was done using 100 000 random points sampled across the study area, and the bioclimatic
137 variables were centred and scaled prior to analysis. We retained rasters for the first four PCA
138 axes, accounting for 90% of the variation within the climate data (SI Fig 1 and SI Fig 2).

139 The CNRM-CM6-1 model is a widely used and well-validated climate model. It is a fully
140 coupled atmosphere-ocean general circulation model developed by Centre National de
141 Recherches Météorologiques (CNRM) for the sixth generation of the IPCC Coupled Model
142 Intercomparison Project 6 (CMIP6) (Eyring et al. 2016, Voldoire 2019). We used two future
143 CNRM-CM6-1 models for the same 19 bioclimatic variables at the same 30-second resolution
144 for the years 2041-2060 obtained from WorldClim 2.1 (Fick and Hijmans 2017, Voldoire 2019).
145 Shared Socioeconomic Pathway (SSP) models are updates to the previous RCP models. Of the
146 five possible pathways, we chose the following two scenarios: SSP2-4.5 (optimistic, some effort
147 is made to limit warming to around 3 degrees, closest to RCP 4.5) and SSP3-7.0, the middle of

148 road baseline outcome if no changes are made to global climate policy) (Eyring et al. 2016,
149 O'Neill et al. 2017).

150 We then applied the PCA model to each of the two future datasets and again retained the first
151 four rasters for analysis. All future climate rasters were masked using the watershed boundary of
152 the Mojave and Colorado deserts (USGS 2006).

153 *Distribution models*

154 We built SDMs for each plant and ant species using the R package SDMtune (Vignali et al.
155 2020). We used Maxent because it is suitable for use with presence-only data and because it has
156 been shown to work well with even small datasets (Hernandez et al. 2006). We used the Maxnet
157 method of Maxent as described in Phillips et al (2017), which improves previous versions of
158 Maxent by implementing a complementary log-log (clog-log) transformation to produce an
159 estimate of occurrence instead of the estimates of habitat suitability produced by the exponential
160 method because this method models species occurrences as an inhomogeneous Poisson process
161 (IPP) (Phillips et al. 2017).

162 Occurrence points were thinned to one point per raster cell for each species to reduce spatial
163 bias. We generated pseudo-absences by randomly sampling 10000 points from across the study
164 area ('randompoints()', 'dismo' package (Hijmans et al. 2017)). We used random k folds at a value
165 of five to determine which partitions to hold back for cross-validation. We repeated models for
166 each species 40 times each with different subset randomization. We assessed the predictive
167 performance of each model using the area under the receiver operating characteristic curve
168 (AUC). AUC ranges between 0 and 1, where 1 is perfect prediction and 0.5 is the baseline
169 accuracy of a binary outcome. Models with AUC values ≥ 0.7 are considered good (Phillips
170 and Dudík 2008). Only species with mean AUC ≥ 0.7 across replicates were retained in the
171 stacked SDMs (SI Table 1 and Table 2, two species of ants were thus excluded due to low AUC:
172 *Camponotus sayi* and *Forelius pruinosus*. All EFN-bearing plant species tested were retained).

173 We predicted each species' distribution across the study area and used the clog-log
174 transformation to obtain a probability of presence between 0 and 1 for each of the 40 model runs.
175 To account for the uncertainty of the SDM predictions, we took the aggregate mean of the 40
176 prediction rasters to form a consensus distribution raster for each species.

177 We then projected each of the 40 model runs for each ant and plant species onto both future
178 climate scenarios. We again took the means of the resulting rasters to determine the final
179 consensus distribution model for each species for each future climate scenario.

180 *Stacking procedures*

181 To create the plant and ant community richness rasters, we stacked the consensus rasters for each
182 community and summed the continuous probabilities. This approach to creating stacked SDMs
183 outperforms thresholded binary stacked SDMs and the output is equivalent to species richness
184 (Dubuis et al. 2011, Calabrese et al. 2014, Zurell et al. 2020). We also created predicted future
185 community richness rasters for each community under each future climate change scenario.

186 *Distributional relationship between EFN plants and ants*

187 We sampled 5000 random points from the plant and ant community stacked SDMs. We
188 calculated Pearson's correlation coefficient to quantify the strength of the association between
189 the species richness of the two communities.

190 Correlations in species richness between the two communities can arise from shared
191 environmental preferences, thus we used variance partitioning to determine the independent and
192 shared components of ant community richness variation explainable by EFN-bearing plant
193 species richness and climate ('varpart', vegan package, Oksanen et al. 2010). The four PCA axes
194 were used as the climate predictor matrix and EFN plant community richness was used as the
195 second predictor.

196 We then evaluated if EFN plant richness influences ant species distributions by fitting two
197 additional sets of SDM for each ant species: the first with the EFN plant community richness
198 raster included as a predictor alongside the climate variables, and the second with the EFN plant
199 community as the sole predictor. We followed all the same procedures as the climate-only
200 models.

201 We tested for differences in the predictive performance of the three sets of models by fitting
202 linear mixed models (LMM) using the test AUC as the response variable and the ant species as a
203 random effect (glmmTMB, Brooks et al. 2017). We used the model type (climate, climate+EFN

204 or EFN only) as the predictor. All model runs (40) for each ant species were included in the
205 models and the species was included as a random effect.

206 *Comparing environmental responses between ant and plant communities*

207 We calculated the variable importance of each of the four climate predictors (PC1 through PC4)
208 for each ant and plant species using 50 permutations ('varimp' function in SDMtune). The
209 function randomly permutes one variable at a time and computes the decrease in training AUC.
210 The result is normalized to percentages for each predictor variable (Vignali et al. 2020).

211 We tested for differences in ant and EFN plant environmental needs by contrasting the variable
212 importance scores. For each climate variable (PC1 through PC4), we conducted a t-test between
213 the ant species' scores and the EFN plant species' scores.

214 *Understanding ant and plant community-level responses to climate change*

215 To understand how climate change will impact future diversity patterns across the Mojave and
216 Colorado deserts, we tested for shifts in ant and plant communities' richness distributions for
217 each future climate change scenario. These, and all subsequent analyses for future distributions
218 used the climate-only SDMs. Using 5000 random points, we extracted the species richness for
219 both communities under each scenario. We fit separate LMM for ants and plants each with the
220 scenario (present, SSP 245 and SSP 370) as the predictor and species richness as the response.
221 The pixel identifier was included as a random effect. We used emmeans (Lenth et al. 2018) to
222 contrast the three scenarios.

223 To test if the plant and ant communities become mismatched due to species-specific differences
224 in responses to climate change, we calculated the geographic overlap between each ant and plant
225 species in the present and for both climate scenarios using Schoener's D niche overlap index
226 ('calc.niche.overlap', ENMeval package, Kass et al. 2021). We then used paired t-tests to test for
227 differences in overlap between the present and each of the future scenarios.

228 *Understanding species-specificity in response to climate change*

229 We conducted a post hoc investigation to explain the observed variation in the responses of
230 individual species to climate change. We chose two possible explanations for species-specific
231 responses to the future climate scenarios: phylogeny and environmental breadth.

232 We individually quantified the change in mean environmental suitability across the study area
233 for each ant and plant species by subtracting the present distribution from the future distribution
234 and calculating the mean pixel value. Negative values represent an average decrease in
235 suitability, and positive values represent an average increase in the study area's environmental
236 suitability.

237 We first asked if phylogeny explains the variation in ant species' distribution shifts in response
238 to climate change. A complete species-level phylogenetic tree for ants is still lacking. We used
239 the tree created by Moreau and Bell (2013). In our study, five genera contained a single species
240 (Table 2). We pruned the tree to a single species for each of these genera. For the remaining
241 genera, we added the missing species as random congeners to the tree for a total of 14 tips (SI
242 Fig 3) We tested for a phylogenetic signal in ant distribution changes by calculating Blomberg's
243 K using the change in environmental suitability for each ant species ('phytools', Revell 2012).
244 This method permutes values among the tips of the phylogenetic tree and compares the values to
245 those from a Brownian motion model of evolution (the variance in values is proportional to the
246 tree branch length) (Münkemüller et al. 2012).

247 Environmental breadth is the range of environmental conditions that a species uses (Sexton et al.
248 2017). Environmental breadth metrics measure the uniformity of the geographic distribution of
249 environmental suitability scores for a species (Warren et al. 2021). We calculated Levins' (1968)
250 metric of environmental breadth i.e., the spatial heterogeneity of the distribution of suitability
251 scores ('raster.breadth', ENMtools, Warren et al. 2021). We then calculated Pearson's correlation
252 between environmental breadth and the difference in suitability under each climate change
253 scenario for each species within the ant and plant communities. We additionally tested for
254 phylogenetic signal in environmental breadth for the ant community.

255 All analyses were done using R version 4.3.1 (R Core Team 2023).

256 **Results**

257 *Distributional relationship between EFN plants and ants*

258 Ant species richness was positively correlated with EFN plant species richness across the
259 Mojave and Colorado Deserts (Pearson's $r = 0.765$, $p < 0.001$). Variance partitioning revealed that
260 EFN plant species richness independently explained 50% of the variation in ant species richness.

261 Climate and EFN plant species richness jointly explained 20% of the variation in ant species
262 richness, and climate explained 9% of the variation independently.

263 Ant species distribution models that included EFN richness as a predictor alongside climate
264 performed significantly better in terms of test AUC than models built with only climate (Figure
265 2, GLMM: coef = 0.014 ± 0.003 SD, $z = 5.18$, $p < 0.001$). Climate-only ant SDMs outperformed
266 models built using only EFN plant richness as a predictor (Figure 2, GLMM: coef = $-0.04 \pm$
267 0.003 SD, $z = -13.04$, $p > 0.001$). The EFN-only models were not tractable for three ant species
268 (*C. fragilis*, *F. mccooki* and *M. testaceus*). Distribution models for each ant and plant species
269 with occurrence points overlaid are available in SI Fig 4 and 5.

270 *Comparing environmental responses between ant and plant communities*

271 The bioclimatic variables with the largest impact on the PC1 gradient were related to temperature
272 and precipitation (e.g., Maximum temperature of warmest month, mean temperature of warmest
273 quarter, annual precipitation, precipitation of driest quarter, SI Fig. 1 and 2). The PC1 gradient
274 ranges from warmer/drier to cooler/wetter and can be characterized as an aridity gradient (SI Fig.
275 1 and 2). The major bioclimatic contributors to the PC2 gradient were related to the variation in
276 temperature and precipitation (e.g., temperature annual range, precipitation seasonality and
277 temperature seasonality, SI Fig. 1 and 2).

278 The relative importance of the climatic predictors differed between the ant and plant
279 communities. The PC1 gradient made a significantly larger contribution to the ant species
280 models than the plant species models (t-test, ant mean = 33.12, EFN mean = 13.45, $t = 2.33$, $df =$
281 17.2 , $p = 0.03$). However, the PC2 gradient made a significantly larger contribution to the EFN
282 plant species models (t-test, mean ants = 23.2, mean EFN plants = 43.57, $df = 14.2$, $p = 0.018$).
283 Precipitation frequency is a key environmental driver for desert plant communities (Reynolds et
284 al. 2004).

285 *Consequences of climate change for mutualist communities*

286 EFN plant and ant species richness were both projected to decline across the Mojave and
287 Colorado Deserts due to a changing climate (Figure 3, GLMM: Chisq = 2115, $p < 0.001$,
288 emmeans, present – SSP 245: est = 0.036, $p < 0.001$; SSP 370: est = 0.039, $p < 0.001$). Richness
289 declines were significantly greater under the SSP 370 scenario, i.e., the more severe scenario,

290 than the SSP 245 scenario for both communities (emmeans, plants: est = 0.03, t = 3.59, p =
291 0.001; ants: est = 0.038, t = 5.27, p < 0.001). The western part of the Mojave Desert (Figure 3)
292 was predicted to gain both EFN and ant species; however, those areas had low species richness
293 for both communities during the present scenario. Across the Mojave and Colorado Deserts,
294 there was an increase in temperature variability with a decrease in precipitation variability (SI
295 Fig 6). Combined with the warming trend, this suggests an increase in extreme heat events. The
296 decrease in precipitation variability suggests that it will become more uniformly dry.

297 Geographic overlap between ants and plants (Shoener's D) significantly decreases under both
298 climate change projections for future distributions (Figure 4, 245 paired t-test: mean difference =
299 0.03, t = 6.24, df = 153, p < 0.001; 370: mean difference = 0.03, t = 6.7, df = 153, p < 0.001).

300 *Understanding species-specificity in response to climate change*

301 The response of species within the ant community to future climate change were more variable
302 than the responses of the EFN plant community. Mean environmental suitability of the Mojave
303 and Colorado Deserts decreased for eight species of ants but increased for six (SI Table 3). In
304 contrast, mean environmental suitability decreased for all EFN plant species except for *Prosopis*
305 *juliflora* (SI Table 4).

306 More environmentally generalized ant species tended to have increased environmental suitability
307 in the future. The mean difference in suitability between the future scenarios and the present was
308 significantly correlated with environmental breadth (Figure 5, SSP 245: Pearson's cor = 0.61, df
309 = 12, p = 0.019; SSP 370: Pearson's correlation = 0.598, df = 12, p = 0.024). However, this
310 relationship was absent within the EFN plant community (Figure 5, SSP 245: Pearson's cor =
311 0.12, df = 9, p = 0.73; SSP 370: Pearson's cor = 0.095, df = 9, p = 0.78). There was no
312 significant difference in mean environmental breadth between the EFN plant and ant
313 communities (t.test: mean ants = 0.63, plants = 0.52, t = 1.37, p = 0.18).

314 There was not a phylogenetic signal for environmental breadth (Blomberg's K = 0.56, p = 0.3)
315 nor for the mean change in suitability for ants (SSP245: Blomberg's K = 0.61, p = 27; SSP 370:
316 Blomberg's K = 0.59, p = 0.28).

317

318 **Discussion**

319 In this study, we analyzed the climatic factors that drive the current and potential future
320 distributions of two mutualistic species guilds. The hypothesis that EFN mutualisms couple plant
321 and ant communities together in space but become decoupled with climate change was
322 supported. We found that including the EFN-bearing plant community as a predictor, alongside
323 climate, improved the predictive performance of SDMs for ants; however, the actual effect size
324 was relatively small. Thus, the EFN-bearing plant community is an important driver of the
325 geographic distribution and diversity of their mutualists, but climate-based SDMs are suitable to
326 model the distribution of these ant communities. Our study highlights that climate change will
327 negatively impact nearly all EFN-bearing plant species and approximately half of the associated
328 ant communities of the Mojave and Colorado Deserts by reducing habitat suitability for both
329 guilds. In contrast, environmental suitability and thus range size is expected to increase for 42%
330 of the ant species. Nonetheless, pairwise geographic overlap between ant and EFN-bearing plant
331 species is expected to decrease, demonstrating that the range increases of some species within
332 the ant guilds do not compensate for the range losses of the plants. The dispersal capacities of
333 these EFN-bearing species are relatively low (Martínez-Berdeja 2015) making it unlikely that
334 these plant species can disperse beyond the desert study area in these timelines. Thus, the
335 potential for this mutualism to persist under climate change will decrease because of this spatial
336 mismatch as well as the capacity for either guild to respond to shifted climates in space.

337 This synthesis revealed that more environmentally generalized ant species benefit from the
338 changing climate, whereas the EFN-bearing plants are negatively impacted more uniformly
339 despite their environmental generalization. Species with a broader environmental niche are
340 generally expected to cope better with a changing climate because they possess greater
341 ecological tolerance than those with narrower niches (Thuiller et al. 2005, Carscadden et al.
342 2020). Our results suggest that caution is needed when comparing environmental breadth across
343 taxa on different trophic levels, as these groups often have distinct physiological strategies. We
344 found that the environmental breadth of these ant species was unrelated to their phylogeny.
345 While our results do not preclude the role of phylogeny at larger scales, they highlight the role of
346 local adaptation within this desert ant community. While the PC1 and PC2 gradients decrease
347 across the deserts, the PC4 gradient exhibits both increases and decreases in the future (see SI

348 Figure 6). The PC4 gradient is marked by increases in the mean temperature of the wettest
349 quarter, precipitation during the warmest quarters, and isothermality (SI Fig 2). Most
350 precipitation in the Mojave Desert occurs during the colder winter months (WRCC, 2024), which
351 suggests that some environmentally generalized ant species may benefit from the warming
352 winter temperatures.

353 Interactions between species can cause correlations in species richness between communities
354 (Gaston 1996). The interactions between the ant species and EFN-bearing plants in our study
355 were established a priori (e.g. Pemberton 1988, Chamberlain and Holland 2009); however, we
356 found multiple lines of evidence for a relationship between the diversity of the two communities
357 across the Mojave and Colorado Deserts. This includes a strong correlation between the diversity
358 of the EFN-bearing plant community and the diversity of the ant community. Additionally, the
359 variation in EFN-bearing plant community diversity explained a large component of the variation
360 in the diversity of the ant community, independent of their shared environmental needs. Meta-
361 analyses have shown that plant richness supports animal richness, and these relationships are
362 stronger between trophically linked arthropods and plants (Castagneyrol and Jactel 2012) and
363 plant-pollinator mutualisms (Kral-O'Brien et al. 2021). Globally, EFN-bearing plant diversity
364 clusters with ants in several biogeographic regions (Luo 2022) but these relationships are not
365 well studied in arid ecosystems because there are relatively few surveys of EFN plant diversity in
366 deserts. Collectively, our results join those of the literature suggesting that the benefits of
367 maintaining EFN-bearing plant diversity will extend beyond that focal community into their ant
368 mutualists with implications for ecosystem functioning.

369 Considering interspecies dependencies is necessary when considering the full extent of climate
370 change impacts. SDMs that contain species interactions can help identify which species rely
371 more heavily on their partners for persistence within an ecosystem (Filazzola et al. 2018).
372 Including the EFN plant community as a predictor into the ants' SDM improved their predictive
373 performance on average; however, we used richness as the measure of the plant community and
374 therefore our results reveal which species' distributions depend more strongly on the diversity of
375 their mutualists (Figure 2). Generalized interactions are expected to be more resilient to climate
376 change because species can switch interaction partners. However, we found that spatial overlap
377 between mutualists decreases significantly in the future. Thus, the capacity for the generalized

378 nature of this interaction to buffer it is constrained by the climatic responses of its participant
379 species.

380 **Literature Cited**

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552 **Data availability statement**

553 Statistical workflows and code will be published in reproducible documents along with the
554 derived data.

555 **Figures and Tables**

556 Table 1: List of the 11 Mojave Desert EFN-bearing plant species included in this study.

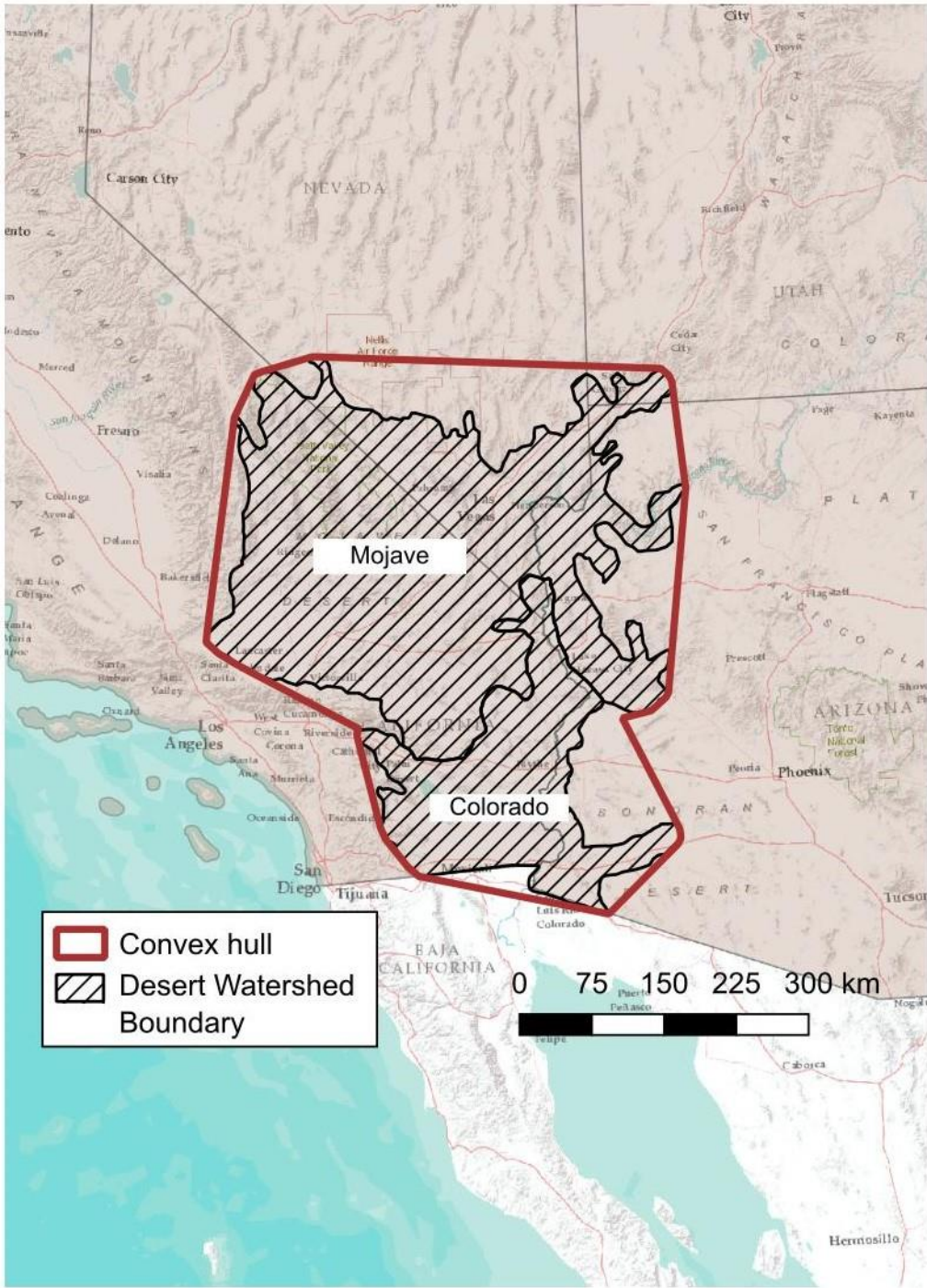
Species name	Common names	Family
<i>Cylindropuntia acanthocarpa</i>	Buckhorn cholla	Cactaceae
<i>Cylindropuntia echinocarpa</i>	Silver cholla	Cactaceae
<i>Senegalia greggii</i>	Catclaw acacia	Fabaceae
<i>Fouquieria splendens</i>	Ocotillo	Fouquieriaceae
<i>Chilopsis linearis</i>	Desert willow	Bignoniaceae
<i>Opuntia basilaris</i>	Beavertail prickly pear	Cactaceae
<i>Cylindropuntia bigelovii</i>	Teddy-bear cholla	Cactaceae
<i>Ferocactus cylindraceus</i>	California barrel cactus	Cactaceae
<i>Prosopis juliflora</i>	Mesquite	Fabaceae
<i>Prunus fasciculata</i>	Desert almond	Rosaceae
<i>Prunus fremonti</i>	Desert apricot	Rosaceae

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558 Table 2: List of 14 Mojave Desert EFN-associated ant species included in this study.

Ant species names	Subfamily
<i>Solenopsis xyloni</i>	Myrmicinae
<i>Forelius mccooki</i>	Dolichoderinae
<i>Crematogaster depilis</i>	Myrmicinae
<i>Dorymyrmex bicolor</i>	Dolichoderinae
<i>Dorymyrmex insanus</i>	Dolichoderinae
<i>Camponotus fragilis</i>	Formicinae
<i>Camponotus ocreatus</i>	Formicinae
<i>Camponotus semitestaceus</i>	Formicinae
<i>Myrmecocystus kennedyi</i>	Formicinae
<i>Myrmecocystus testaceus</i>	Formicinae
<i>Myrmecocystus flaviceps</i>	Formicinae
<i>Myrmecocystus mimicus</i>	Formicinae
<i>Pheidole vistana</i>	Myrmicinae
<i>Liometopum luctuosum</i>	Dolichoderinae

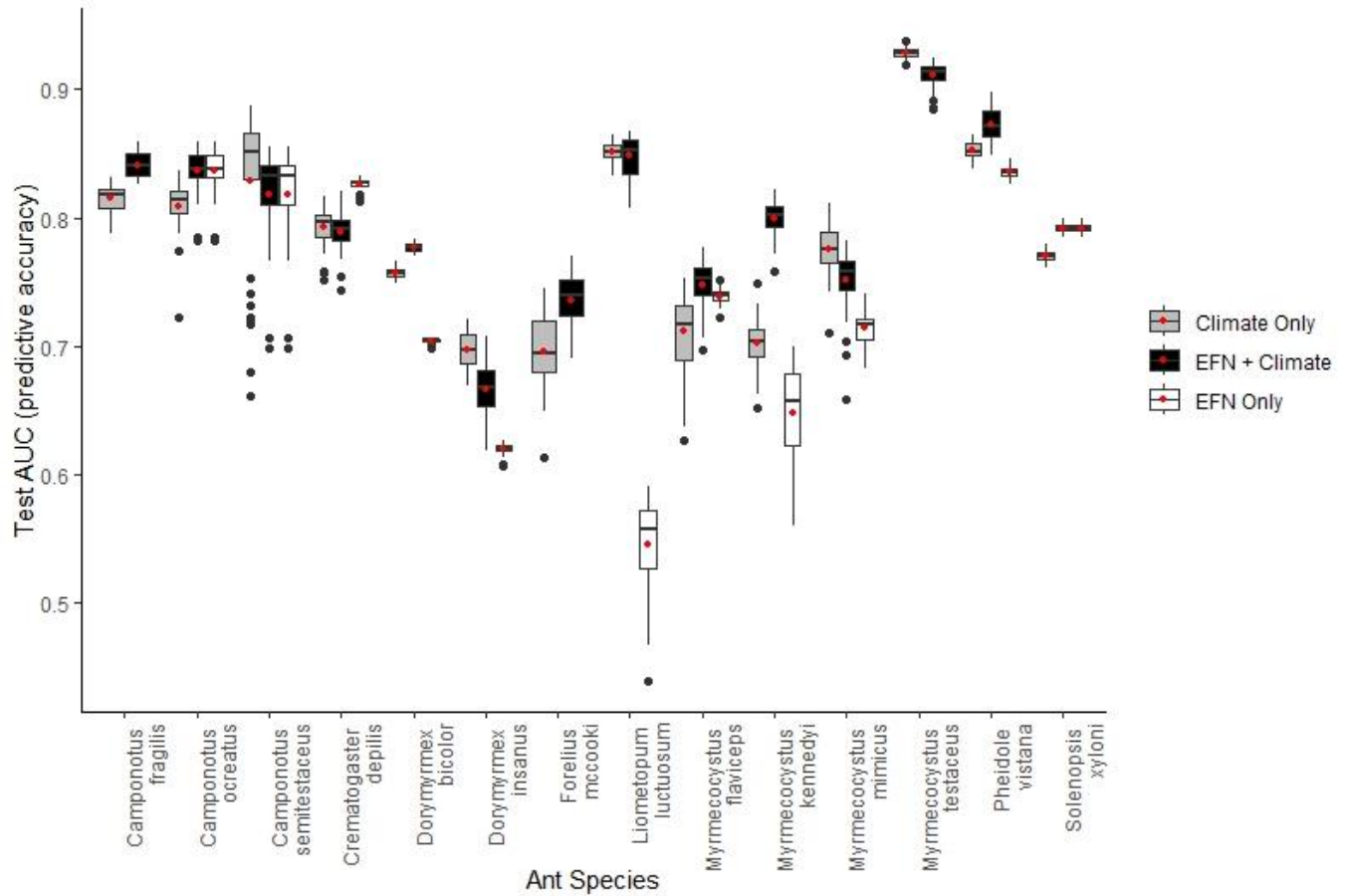
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561 Figure 1: Map of Southwestern USA showing the Mojave and Colorado Deserts. The main study
 562 area used was the watershed boundary from the United States Geological Survey (USGS).

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566 Figure 2: Boxplots comparing the predictive performance of ant species distribution models built
 567 using only climatic, climatic predictors or only extrafloral nectary (EFN) richness as a predictor.
 568 Lines on boxplots show median values, and the means are represented by the red diamonds. The
 569 variation in performance is summarized from 40 model runs per species, per set of predictors.

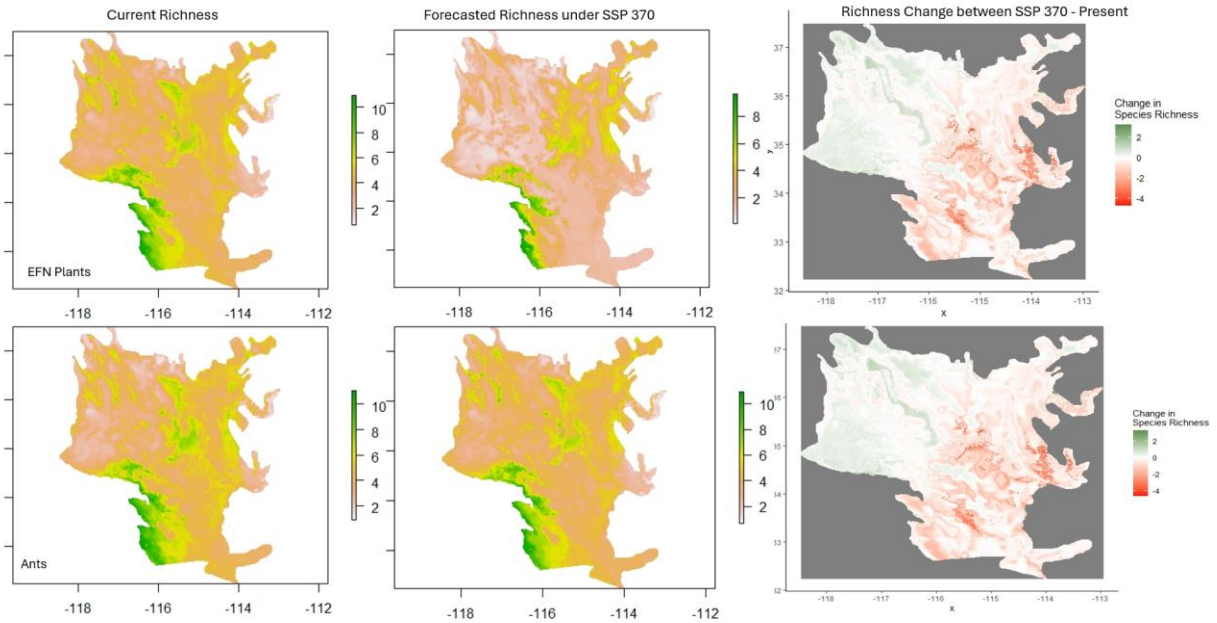
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576 Figure 3: Current and forecasted species richness of EFN-bearing plants (top row) and their
 577 associated ant species (bottom row) across the Mojave and Colorado deserts, as well as the
 578 predicted change in richness.

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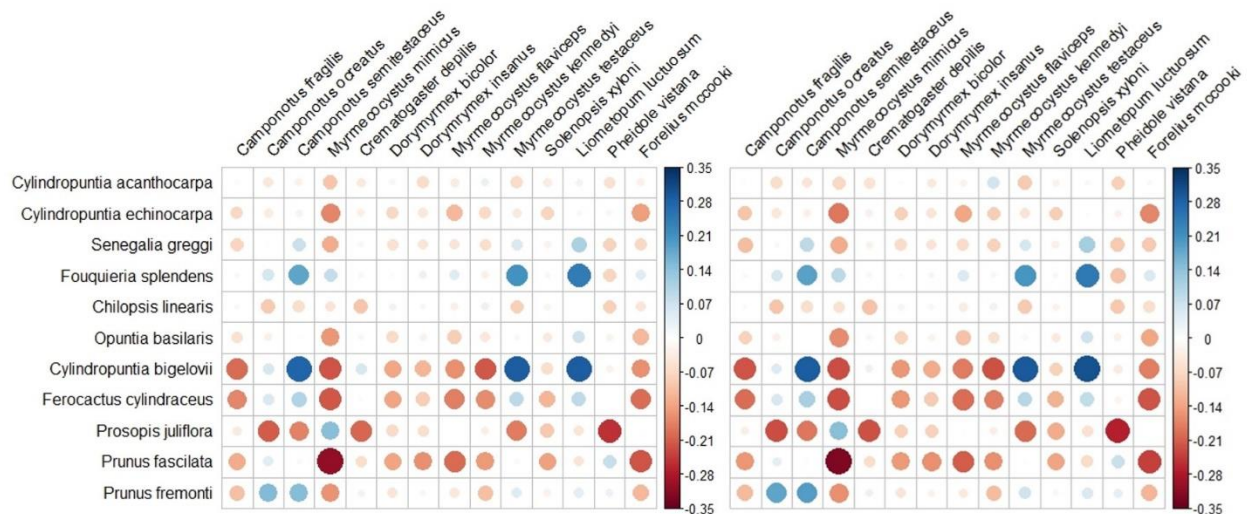
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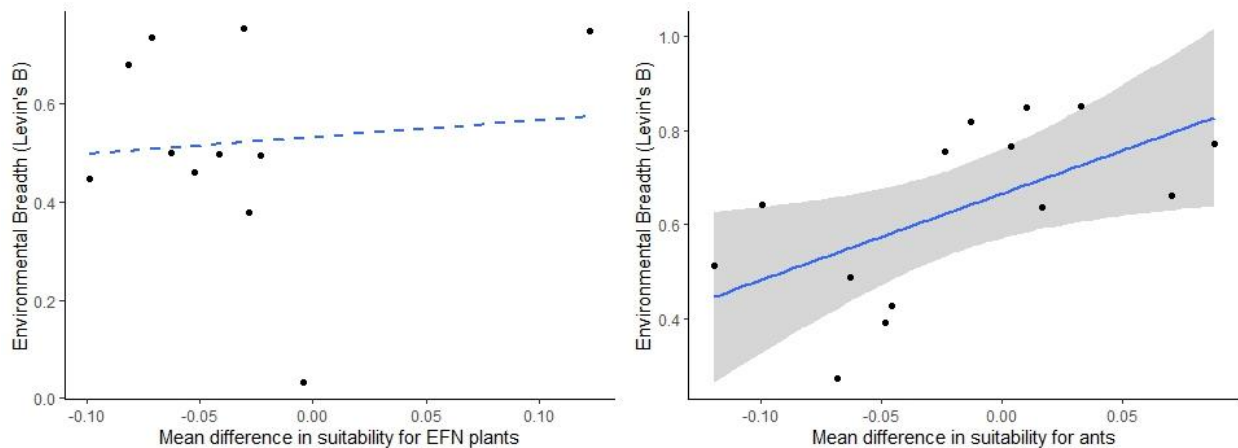
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591 Figure 4: Proportional change in interspecific overlap of distribution ranges (Schoener's D niche
 592 overlap index) between the periods 1970-2000 and 2041-2060 for two climate scenarios: SSP
 593 245 (left) and SSP 370 (right). Negative values in red indicate a decrease in range overlap
 594 between species over the time periods; blue indicates an increase in range overlap, and zero
 595 values in white indicate no changes to overlap.

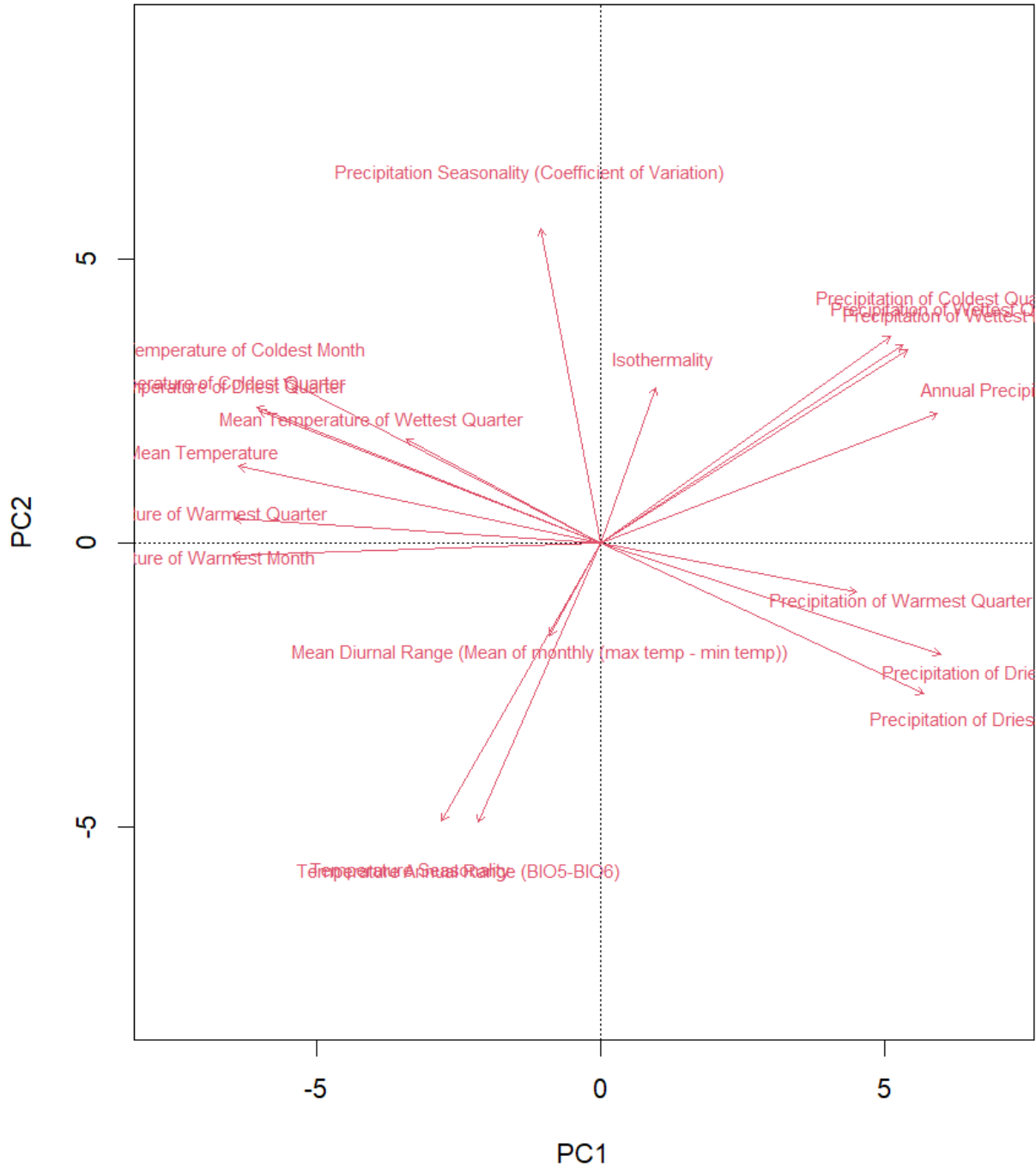


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597 Figure 5: Correlations between environmental breadth and suitability changes for the EFN plant
 598 and ant communities of the Mojave and Colorado deserts. The solid trendline denotes a
 599 significance at the $p < 0.05$ level and the dashed line denotes an insignificant relationship.

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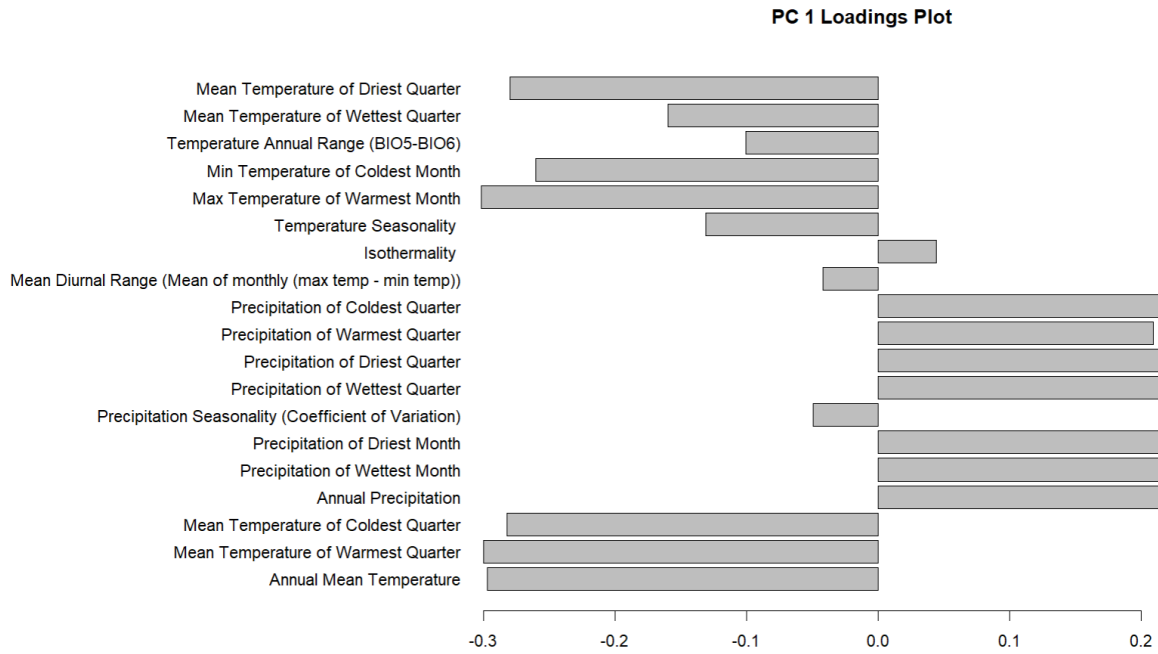
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605 Figure 1: PCA of the 19 bioclimatic variables across the Mojave and Colorado deserts. The first
606 four PCA axes explained 90% of the total bioclimatic variation.

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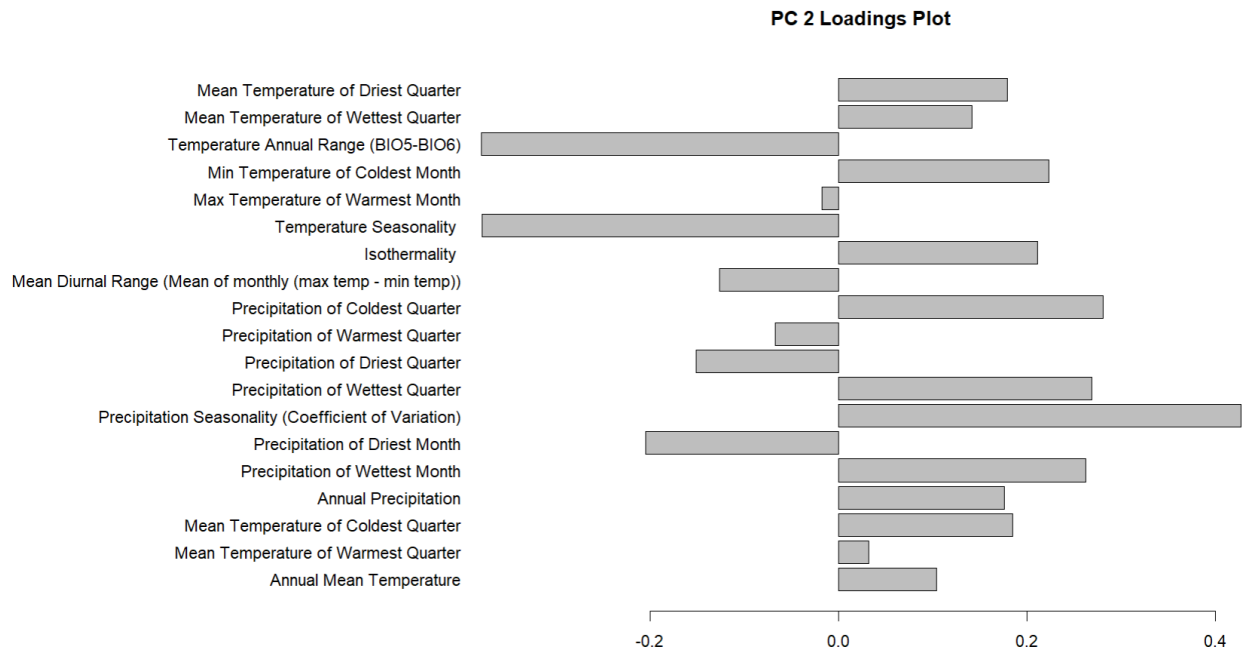
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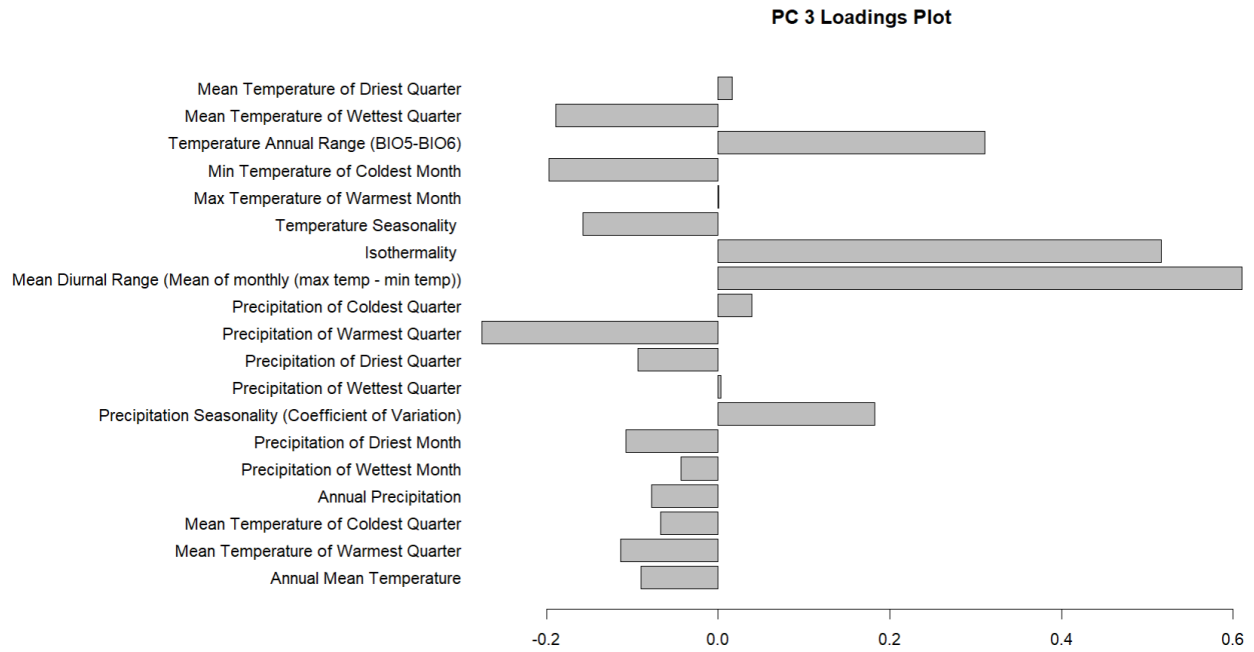
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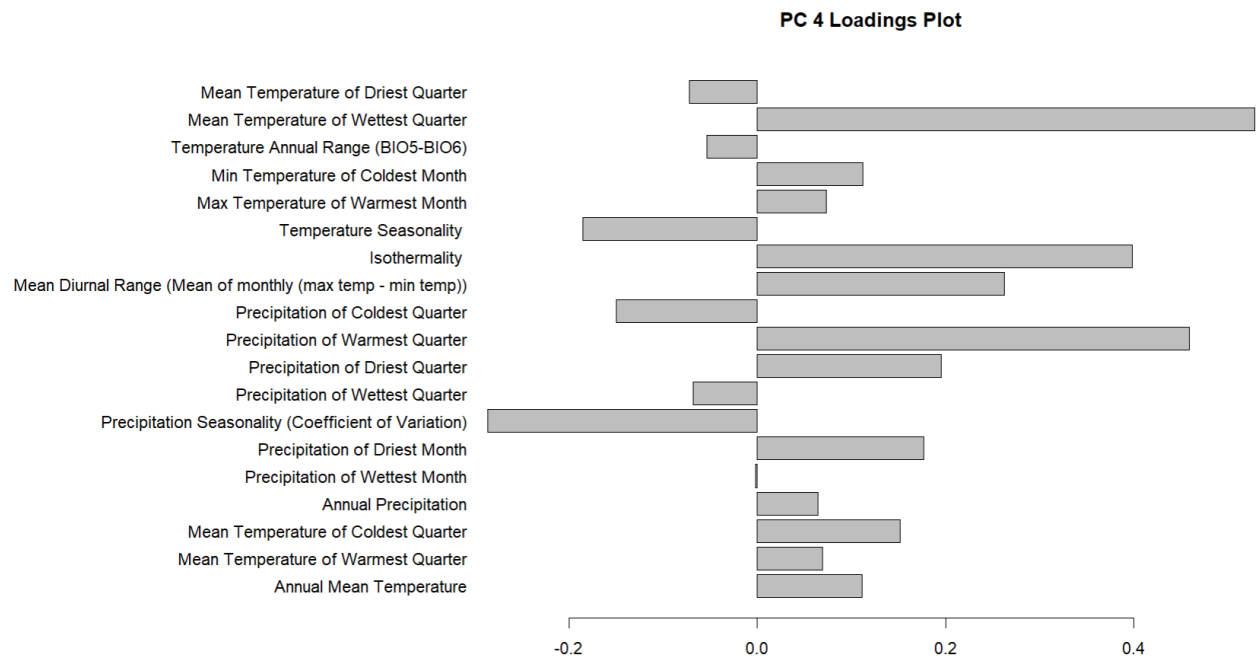
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618 Figure 2: Loadings for each of the four PCA axes in the study.

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Table 1: Maxent species distribution model performance measures for each EFN bearing plant species used in the study and the number of occurrences after thinning included in the model. Area under the curve (AUC) ranges between 0 and 1, where 0.5 is the baseline performance.

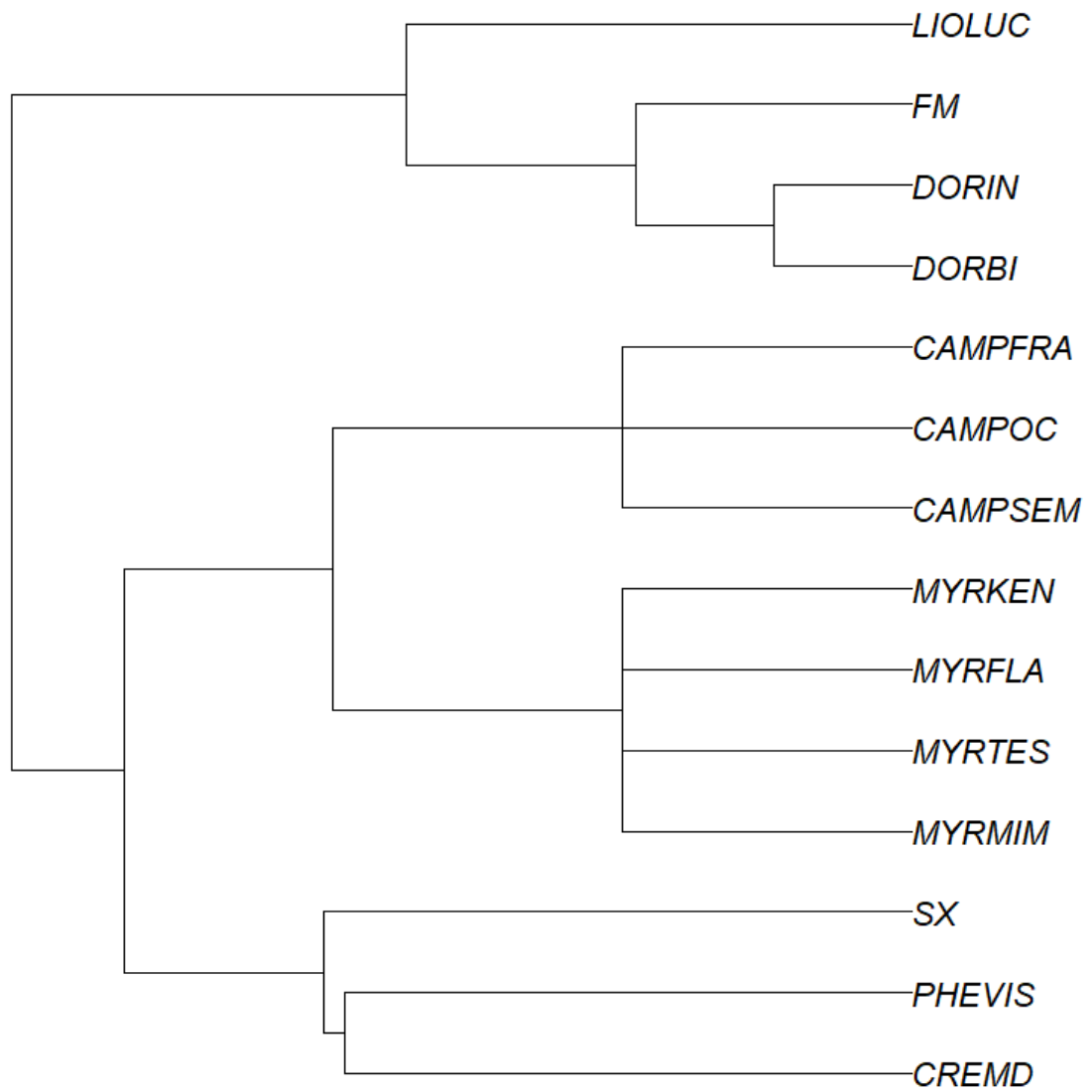
Latin binomial	Occurrences after thinning	AUC (Mean \pm SD)	
<i>Cylindropuntia acanthocarpa</i>	1563	0.86 \pm 0.000	629
<i>Cylindropuntia echinocarpa</i>	3243	0.79 \pm 0.000	630
<i>Senegalia greggii</i> (previously <i>Acacia</i>)	1747	0.87 \pm 0.000	631
<i>Fouquieria splendens</i>	2298	0.83 \pm 0.000	632
<i>Chilopsis linearis</i>	1220	0.79 \pm 0.001	633
<i>Opuntia basilaris</i>	4666	0.78 \pm 0.000	634
<i>Cylindropuntia bigelovii</i>	125	0.87 \pm 0.002	635
<i>Ferocactus acanthodes</i> syn <i>cylindraceus</i>	3166	0.86 \pm 0.000	636
<i>Prosopis juliflora</i>	21	0.73 \pm 0.03	637
<i>Prunus fasciculata</i>	798	0.84 \pm 0.001	
<i>Prunus fremontii</i>	437	0.97 \pm 0.000	

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649 Table 2: Maxent species distribution model performance measures for each ant species used in
 650 the study and the number of occurrences after thinning included in the model. Area under the
 651 curve (AUC) ranges between 0 and 1, where 0.5 is the baseline performance. Species with a
 652 score of N/A had too few occurrences to model. Two species, *Camponotus sayi* and *Forelius*
 653 *pruinosis* were excluded due to poor predictive performance.

Ant Species	Occurrences after thinning	AUC (Mean \pm SD)
<i>Brachymyrmex depilis</i>	4	N/A
<i>Camponotus sayi</i>	14	<i>0.6 \pm 0.04 - Excluded</i>
<i>Lasius californicus</i>	5	N/A
<i>Liometopum luctuosum</i>	26	0.85 \pm 0.01
<i>Myrmecocystus mimicus</i>	23	0.78 \pm 0.02
<i>Pheidole vistana</i>	27	0.85 \pm 0.01
<i>Pseudomyrmex apache</i>	10	N/A
<i>Pseudomyrmex gracilis</i>	0 on gbif	N/A
<i>Pseudomyrmex pallidus</i>	11	N/A
<i>Solenopsis xyloni</i>	191	0.77 \pm 0.00
<i>Forelius pruinosis</i>	78	<i>0.62 \pm 0.02 - Excluded</i>
<i>Forelius mccoeki</i>	27	0.7 \pm 0.03
<i>Crematogaster depilis</i>	38	0.79 \pm 0.02
<i>Dorymyrmex bicolor</i>	172	0.76 \pm 0.00
<i>Dorymyrmex insanus</i>	42	0.7 \pm 0.01
<i>Camponotus fragilis</i>	32	0.81 \pm 0.01
<i>Camponotus semitestaceus</i>	15	0.83 \pm 0.06
<i>Camponotus ocreatus</i>	45	0.81 \pm 0.02
<i>Myrmecocystus kennedyi</i>	30	0.7 \pm 0.02
<i>Myrmecocystus testaceus</i>	15	0.93 \pm 0.00
<i>Myrmecocystus flaviceps</i>	26	0.71 \pm 0.03

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659 Figure 3: Pruned phylogenetic tree of ant species based on Moreau and Bell 2013.

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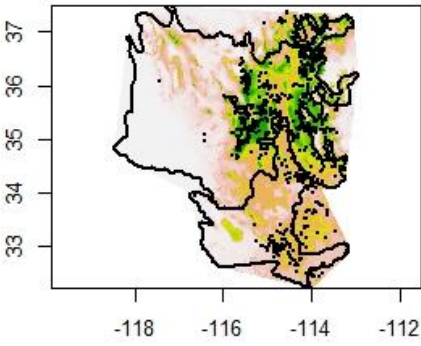
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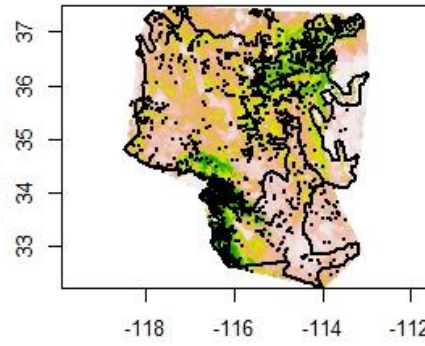
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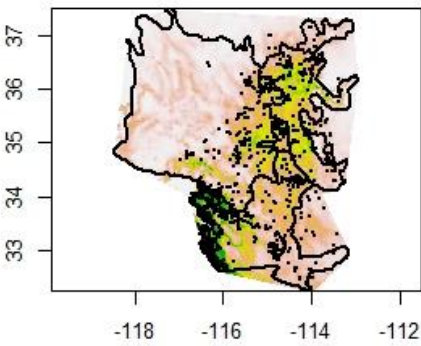
Cylindropuntia acanthocarpa



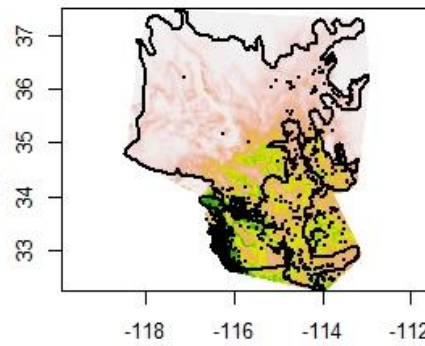
Cylindropuntia echinocarpa



Senegalia greggii

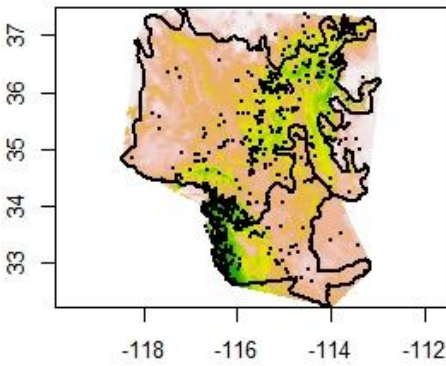


Fouquieria splendens

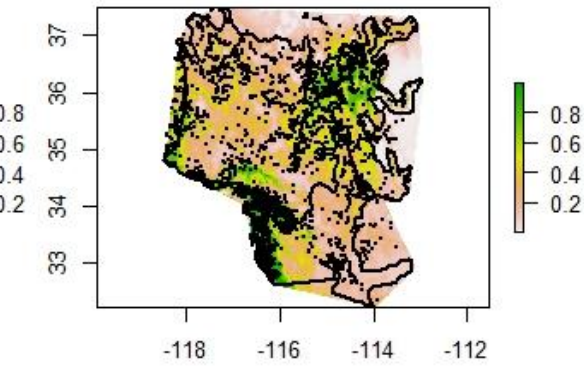


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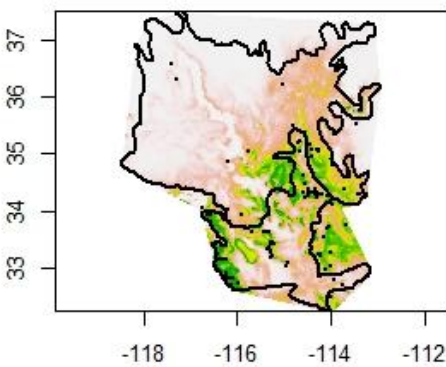
Chilopsis linearis



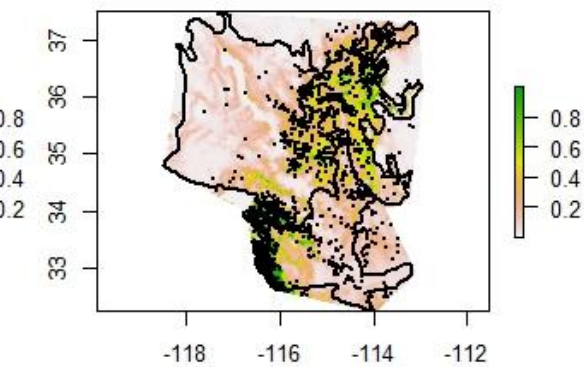
Opuntia basilaris

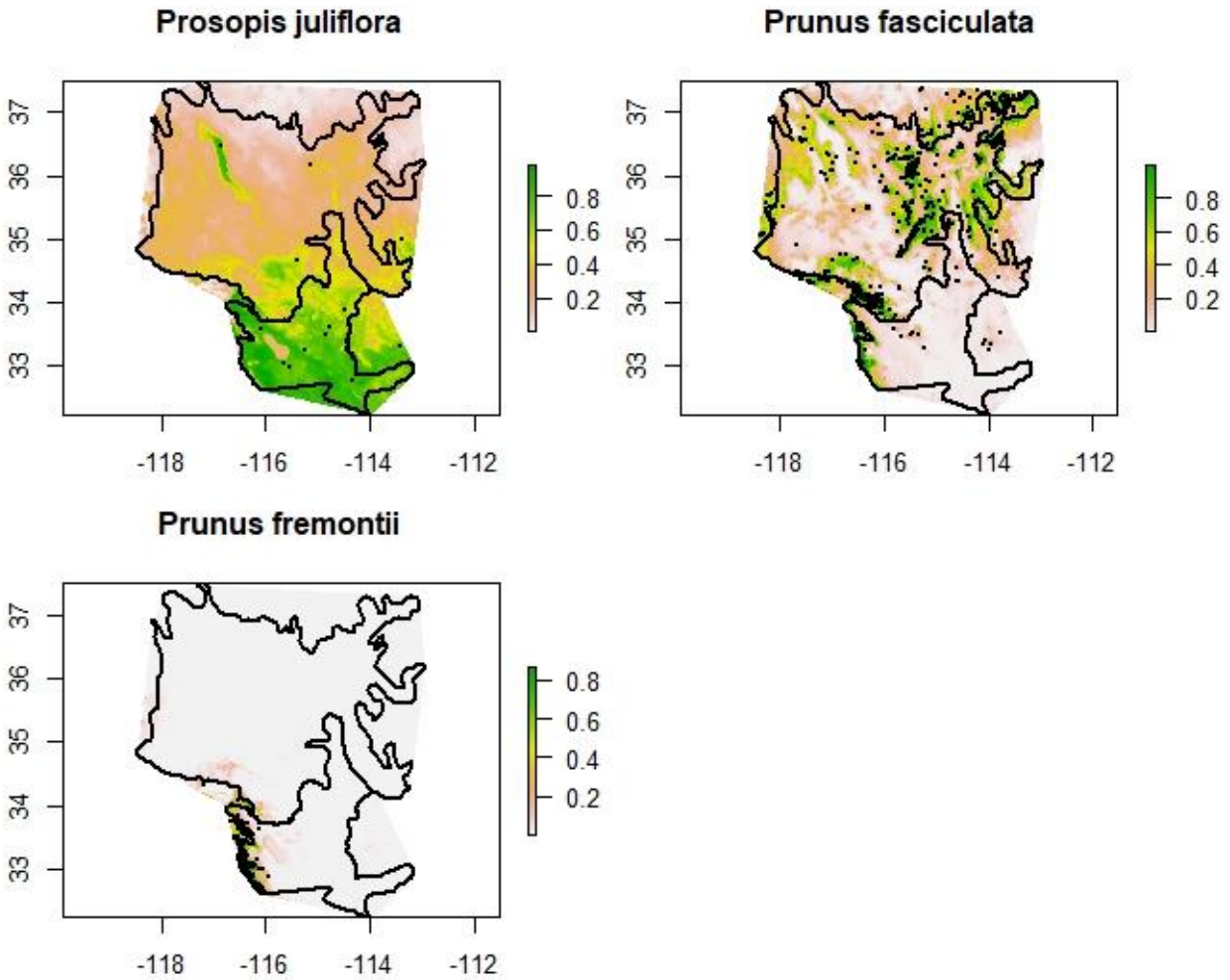


Cylindropuntia bigelovii



Ferocactus cylindraceus





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670 Figure 4: Consensus prediction maps for EFN-bearing plant species of the Mojave and Colorado
 671 deserts. Points are the thinned occurrences extracted from GBIF and the boundary file is the
 672 watershed boundary from USGS.

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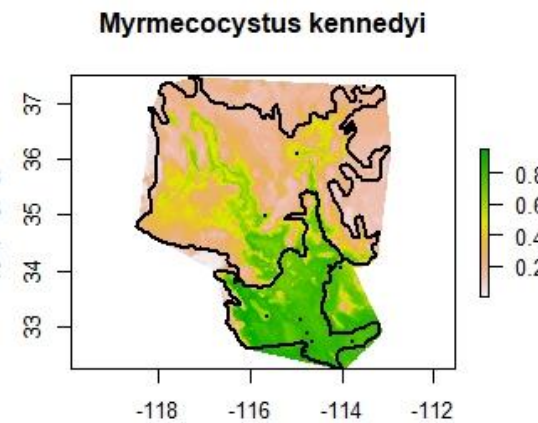
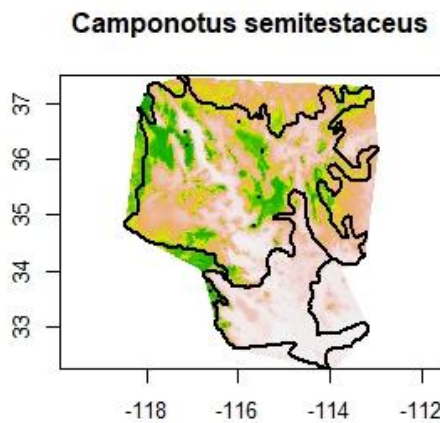
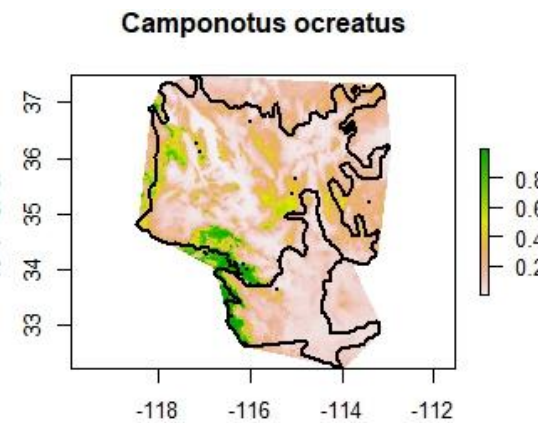
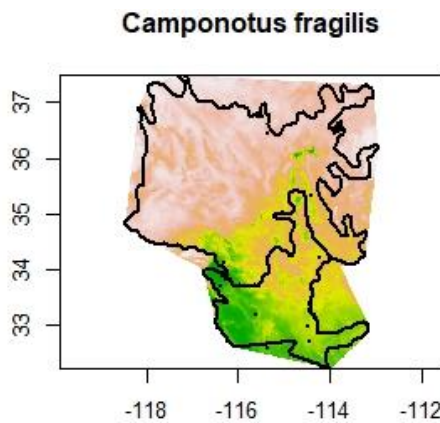
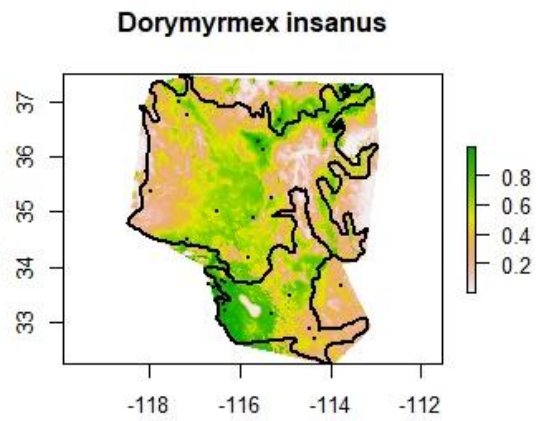
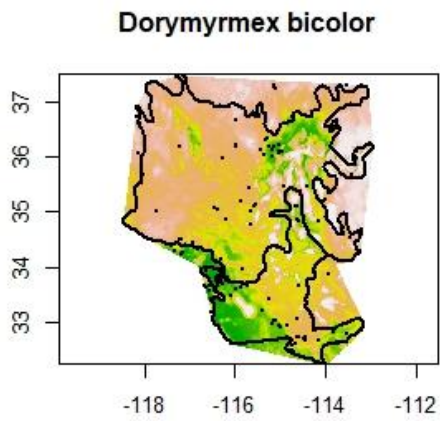
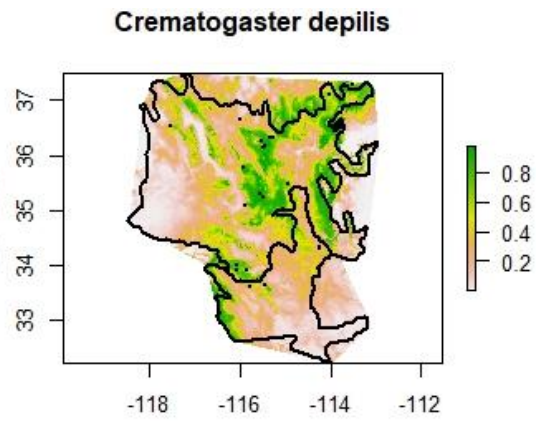
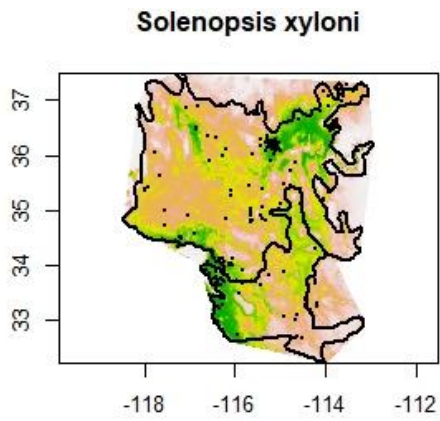
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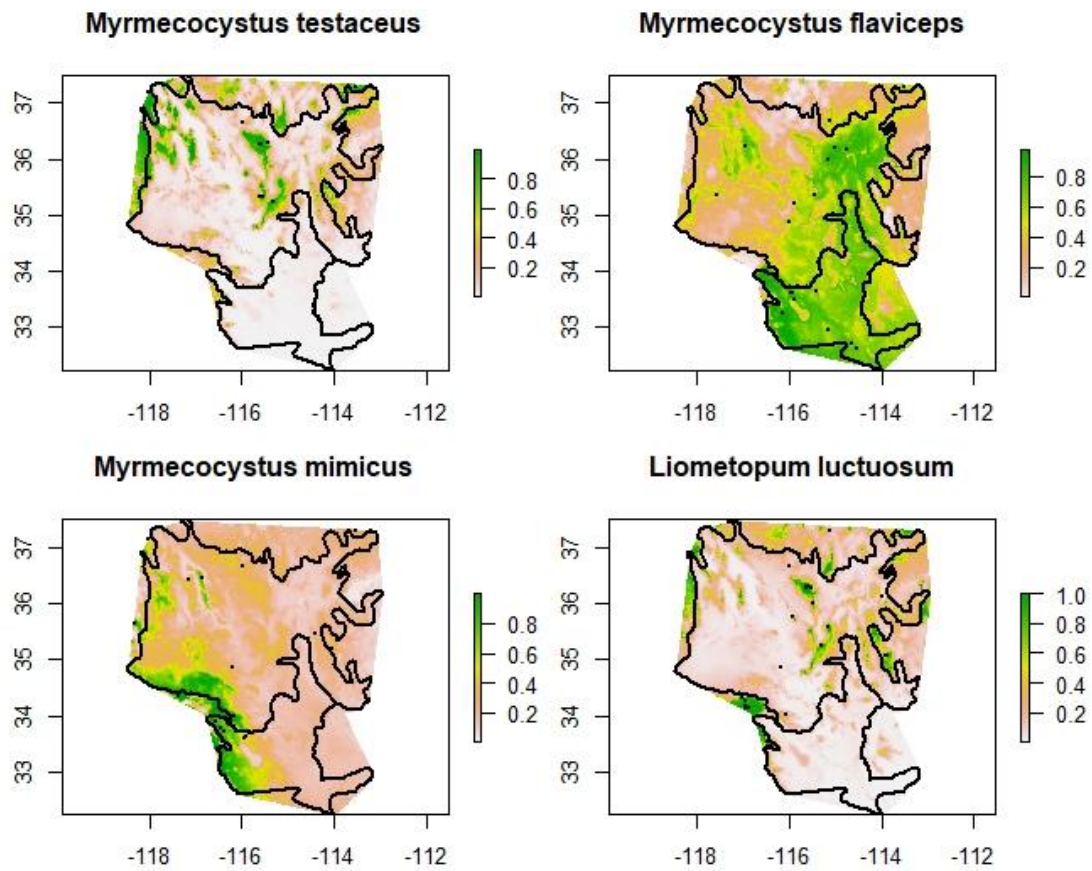
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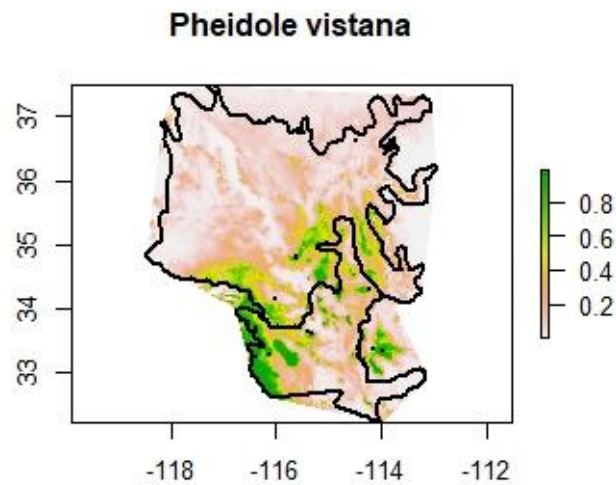


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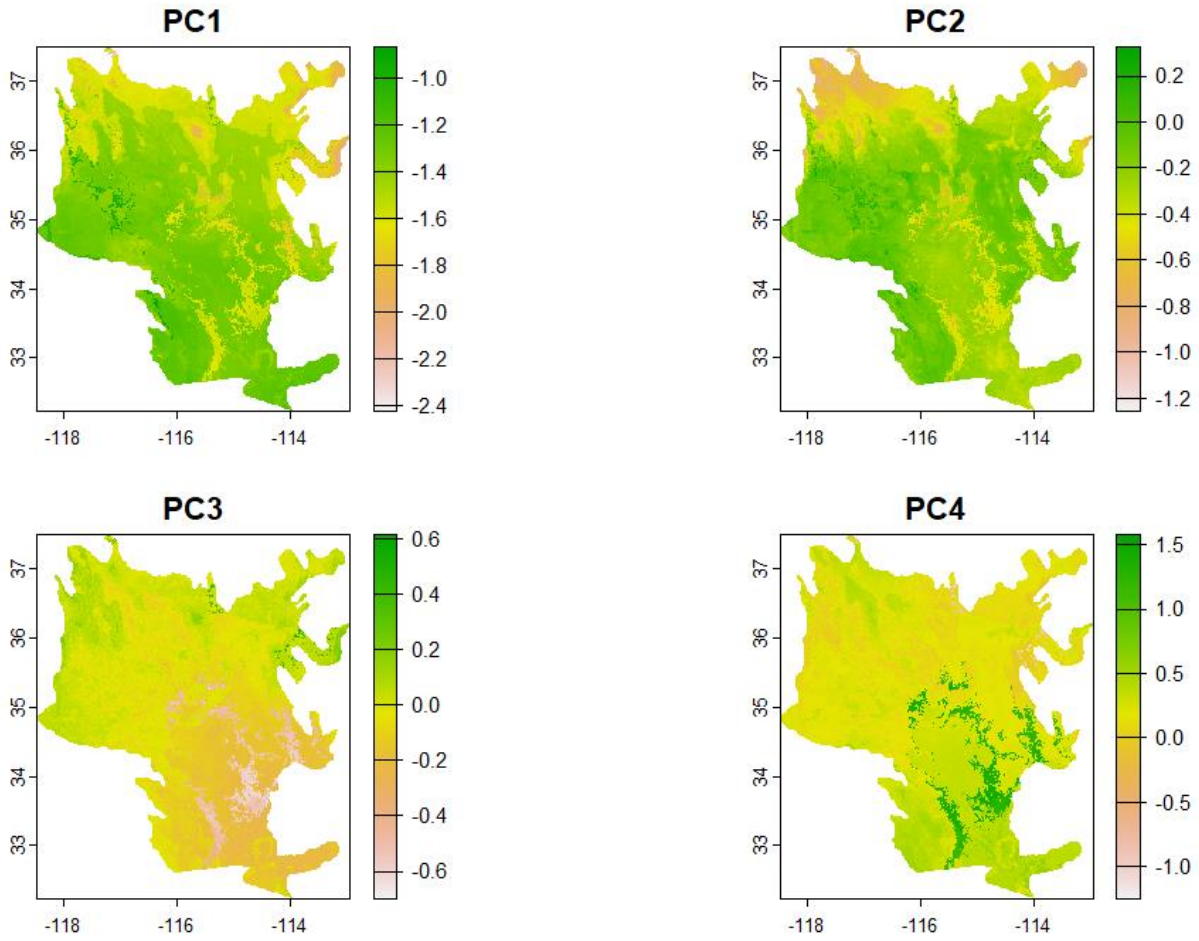


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700 Figure 5: Consensus prediction maps for ant species of the Mojave and Colorado deserts. Points
701 are the thinned occurrences extracted from GBIF and GABI, and the boundary file is the
702 watershed boundary from USGS.

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709 Figure 6: Shifts in the four main environmental gradients between SSP 370 and present
710 conditions.

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Table 3: Mean change in environmental suitability for individual ant species.

Ant species names	Mean difference in future suitability under 245	Mean difference in future suitability under 370
<i>Solenopsis xyloni</i>	-0.012	-0.02
<i>Forelius mccooki</i>	0.027	0.0327
<i>Creumatogaster depilis</i>	-0.09	-0.1
<i>Dorymyrmex bicolor</i>	0.004	0.004
<i>Dorymyrmex insanus</i>	-0.009	-0.013
<i>Camponotus fragilis</i>	0.011	0.017
<i>Camponotus ocreatus</i>	-0.058	-0.062
<i>Camponotus semitestaceus</i>	-0.108	-0.11
<i>Myrmecocystus kennedyi</i>	0.081	0.088
<i>Myrmecocystus testaceus</i>	-0.062	-0.068
<i>Myrmecocystus flaviceps</i>	0.015	0.01
<i>Myrmecocystus mimicus</i>	0.066	0.07
<i>Pheidole vistana</i>	-0.042	-0.046
<i>Liometopum luctuosum</i>	-0.045	-0.048

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Table 4: Mean change in environmental suitability for individual EFN-bearing plant species

Species name	Mean difference in future suitability under 245	Mean difference in future suitability under 370
<i>Cylindropuntia acanthocarpa</i>	-0.049	-0.052
<i>Cylindropuntia echinocarpa</i>	-0.074	-0.082
<i>Senegalia greggii</i>	-0.03	-0.04
<i>Fouquieria splendens</i>	-0.02	0.023
<i>Chilopsis linearis</i>	-0.025	-0.031
<i>Opuntia basilaris</i>	0.06	-0.071
<i>Cylindropuntia bigelovii</i>	0.03	-0.028
<i>Ferocactus acanthodes syn cylindraceus</i>	-0.057	-0.062
<i>Prosopis juliflora</i>	0.11	0.122
<i>Prunus fasciculata</i>	-0.09	-0.099
<i>Prunus fremonti</i>	-0.003	-0.004

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