



## 13 Abstract

14 Climate change is expected to cause widespread shifts in the composition of plant communities.  
15 However, the extent to which these changes will alter the composition and diversity of plant  
16 functional traits is less clear. Here, we assess how climate change may reshape the functional  
17 diversity of 32,996 plant communities by combining data on their traits and realised climatic  
18 niches with future climate projections. We find that under projected climates for the decade  
19 centred on 2070, up to a third of species will experience conditions outside of their current  
20 realised climatic niches. Yet, on average, the loss of these species from communities  
21 represented a potential decay in functional diversity of 9.5%, indicating some functional  
22 redundancy. We found weak evidence that patterns of species replacement, which are  
23 contingent on their realised climate niches, resulted in increased loss of functional diversity  
24 compared with random removal. Patterns of relative functional decay (i.e., projected loss of  
25 functional diversity relative to species loss under future climate) were distinct between woody  
26 and non-woody species, with woody species being at higher risk of declines in functional  
27 diversity, particularly in alpine and woodland communities. These results highlight the  
28 importance of integrating additional metrics, such as functional diversity and functional decay,  
29 into conservation and restoration planning to prioritise elements of biodiversity that help  
30 explain vulnerability to climate change. Using this dimension of biodiversity can help  
31 conservation practitioners identify areas vulnerable to climate change, inform management  
32 actions, and prioritise the planting of key growth forms to restore ecosystem function and  
33 identity.

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## 38 Keywords

39 “biodiversity conservation”, “community ecology”, “ecological restoration”, “functional  
40 redundancy”, “hypervolume”, “plant traits”

## 41 Introduction

42 Climate change is forecast to continue having a widespread impact on the membership and  
43 function of plant communities globally (Franklin et al., 2016). Projecting the composition of  
44 future vegetation is challenging due to the complex interaction between heterogenous  
45 environmental change (Braga & Laurini, 2024) and species’ varied responses due to their  
46 growth forms and functional traits (Verslues et al., 2023). Plant traits underpin fundamental  
47 mechanisms of reproduction, dispersal, adaptation, and stress tolerance (Suding et al., 2008).  
48 By aggregating these attributes, we can capture information about these key functional  
49 properties of an ecosystem using a suite of functional diversity (FD) metrics (Díaz & Cabido,  
50 2001). Predicting the extent and effects of declines in FD under future climates can proactively  
51 inform conservation and restoration practice and help safeguard plant biodiversity and its vital  
52 functions.

53 Plants have persisted through dramatic changes in climate for millennia, primarily through  
54 movement to track suitable conditions for growth and reproduction (Pardi & Smith, 2012)  
55 (Wang et al., 2022). Some plant species may also adapt in situ, especially where their dispersal  
56 capacity and population movement lags behind by the rate of climate change, else become  
57 locally or globally extinct (Corlett & Westcott, 2013a; Jackson & Overpeck, 2000). Given  
58 unprecedented rates of Holocene climate change (Marcott et al., 2013) many plant species are  
59 projected to experience conditions which outpace their capability to adapt or disperse and  
60 widespread extinctions are forecast (Bachman et al., 2024; Corlett & Westcott, 2013a). There  
61 is already extensive documentation of plant species shifting their ranges in response to  
62 anthropogenic climate change (Bradley et al., 2025; Rubenstein et al., 2023; Wiens, 2016).

63 Additionally, experimental evidence from the field attribute climate change as the driver of  
64 shifts in the abundance, identity and diversity of species in plant communities (Elmendorf et  
65 al., 2015; Reich et al., 2022). Although some species increase in abundance in response to new  
66 growing conditions, while others may persist in lower densities despite climate stress, these  
67 compositional changes are still able to underpin substantial changes to ecosystem function  
68 (Vellend et al., 2013). While species-specific predictions are valuable, anticipating the broader  
69 ecological consequences of climate change requires generalisable frameworks which can guide  
70 actionable conservation and restoration strategies at local scales. Focusing on the functional  
71 attributes of species, rather than their taxonomic identity, offers a flexible and generalisable  
72 predictive framework for forecasting vegetation change.

73 Climate related changes in the composition of plant communities will vary depending on the  
74 traits and tolerances of individual species (Kress & Krupnick, 2022; Pacifici et al., 2017).  
75 Functional traits capture the variety of ecological strategies that plants use to grow, reproduce,  
76 and survive in the environment (Li & Prentice, 2024). As such, many traits exhibit associations  
77 with climate (Dell et al., 2011; Moles et al., 2014). As growing conditions change, the rate at  
78 which species are affected may be mediated through the traits that define their adaptive capacity  
79 (Andrew et al., 2022; Kühn et al., 2021), or the traits which shape their ability to disperse and  
80 track suitable climates (Angert et al., 2011). Functional diversity (i.e., the values and  
81 distribution of traits) defines the amount of occupied niche space in a community, which is a  
82 predictor of ecosystem attributes like productivity and resilience (Legras et al., 2018).  
83 Incorporating FD metrics into forecasting climate change impacts on plant communities  
84 enables us to extend and generalise predictions of which *types* of species might be at risk, but  
85 also how their loss may risk the functioning and resilience of the ecosystems they inhabit.  
86 While measures of species diversity have long been used as a tool for directing conservation  
87 planning (Fleishman et al., 2006), there is still a great potential to expand climate change

88 adaptation strategies through the integration of traits and FD (Gallagher et al., 2021; Mammola  
89 et al., 2021; Pollock et al., 2017). Since FD offers a powerful tool to measure aspects of  
90 biodiversity that are sensitive to climate change (Heilmeyer, 2019) and describes ecologically  
91 meaningful processes (Lavorel, 2013), forecasting its decay in response to a changing climate  
92 offers important context for adaptation planning. For instance, predicting spatial patterns of the  
93 loss of FD through potential species loss under future climate change (i.e. functional decay)  
94 allows conservation practitioners to pre-emptively prioritise and protect vulnerable areas and  
95 to devise and prescribe actions for functionally-informed ecological restoration. Updating  
96 conservation strategies with specific advice regarding climate change is becoming an  
97 increasingly important and common practice and is already being applied to assessments of  
98 species vulnerability (Alagador & Cerdeira, 2017), key biodiversity areas (Beier & Brost,  
99 2010), and restoration (Simonson et al., 2021).

100 In this study, we assess how climate change may alter the FD of plant communities by  
101 combining data from floristics plots, species traits, and current and future climate data. We aim  
102 to quantify the climate change-induced decay in community level FD, as it relates to the  
103 potential loss of species and the unique trait space they contribute to their communities.  
104 Specifically, we ask: 1) How much FD may be lost from climate-change induced reductions in  
105 species richness (i.e. functional decay)? 2) How do patterns of climate-change induced declines  
106 in FD and species richness vary between growth forms (woody or non-woody)? And 3) What  
107 are the patterns of functional decay relative to species richness decay spatially, and between  
108 different vegetation types?

## 109 Methods

110 We use a large network of plant community data (floristic plots) from eastern Australia to  
111 estimate the decay of FD due to climate change, based on filtering out species based on the  
112 limits of their present realised climate niches relative to projected climate conditions.

113 Calculations of functional decay are derived using the proportion of overlapping trait space,  
114 based on multidimensional hypervolumes, between baseline and future-climate filtered species  
115 lists for each plot (Figure 1).

#### 116 Floristic plot data

117 Floristic plot data were acquired from the Vegetation Condition Benchmarks Dataset  
118 (Somerville et al., 2019) across New South Wales (NSW), Australia, derived from the  
119 Systematic Flora Surveys module of the BioNet Atlas (NSW Office of Environment and  
120 Heritage, 2023). The dataset includes 32,996 floristic survey plots that list all vascular plant  
121 species within a 400m<sup>2</sup> survey area (Figure 1a). This dataset includes plots that represent all  
122 16 broad vegetation classifications in the study area (NSW)(Department of Planning and  
123 Environment, 2017) as it is used to derive condition benchmarks for monitoring and  
124 compliance assessments by government agencies (Somerville et al., 2019). These floristic plots  
125 span baseline climate conditions between 4.7-21°C of mean annual temperature (MAT), and  
126 205-2054 mm of mean annual precipitation (MAP) (Australian Bureau of Meteorology, 2019).  
127 Species names in the plot dataset were standardised against the Australian Plant Census  
128 (Australian National Herbarium, 2023) using the ‘APCalign’ package (Wenk et al., 2024a) to  
129 create a consistent taxonomic backbone prior to integrating additional data sources.

#### 130 Plant trait data

131 Trait data for all species occurring in floristic plots was sourced from the AusTraits database  
132 (Falster et al., 2021; Wenk et al., 2024b)(Figure 1bi). Each species was assigned a category of  
133 woodiness (i.e., woody/non-woody) from Wenk et al. (2024b), and the species means of all  
134 available values for six traits were used to calculate FD: leaf nitrogen per dry mass (mg/g), leaf  
135 area (mm<sup>2</sup>), leaf mass per area (g/mm<sup>2</sup>), maximum plant height (m), seed dry mass (mg), and  
136 wood density (mg/mm<sup>3</sup>). These traits encompass variation in plant resource use (Parkhurst &  
137 Loucks, 1972; Wright et al., 2004), competition (Grime, 1988), and reproduction (Bekker et

138 al., 1998), and have varied but well studied relationships with temperature and precipitation  
139 (Dwyer et al., 2014; Moles et al., 2009; Towers et al., 2024; Wright et al., 2001).

140 Where empirical values were not available for some species-trait combinations, we used gap-  
141 filling procedures to impute trait values, a common method in macroecological studies (Schrodt  
142 et al., 2015; Andrew et al., 2025). Imputation was performed using the R package ‘Rphylopars’  
143 (Goolsby et al., 2017) which uses phylogenetic information in combination with data from  
144 known trait values to estimate missing values across a taxon-trait matrix. We created a  
145 phylogenetic tree for use in imputation using ‘V.PhyloMaker2’ (Jin & Qian, 2022) using  
146 taxonomic information from AusTraits (Falster et al., 2021). To improve the predictions of  
147 gap-filling for leaf and seed traits, two additional predictive leaf traits (leaf width and leaf  
148 length) and four seed traits (fruit length, fruit width, seed length, and seed width) were also  
149 provided to the imputation method.

#### 150 Baseline and future climate data

151 Baseline climate data for the period 1971-2000 was derived from Australian Gridded Climate  
152 Data (AGCD; (Australian Bureau of Meteorology, 2019). MAT and MAP were used as  
153 variables for analysis since they are known to influence plant community composition  
154 (MacArthur, 1972; Moles et al., 2014). The AGCD uses 5km grid cells which were aggregated  
155 using bilinear re-gridding to match the spatial resolution of future climate projections. Future  
156 climate projections were sourced from NARClIM version 2.0 (Di Virgilio et al., 2025), an  
157 ensemble of dynamically downscaled climate models at 10km resolution across NSW. The raw  
158 NARClIM data was bias-corrected against the AGCD data for the period between 1971-2000  
159 to improve compatibility between datasets. For this, raw NARClIM data was changed from a  
160 rotated pole grid to rectilinear using bilinear re-gridding and then bias removed using a quantile  
161 mapping approach. For analysis, MAT and MAP projections for the year 2075 (i.e., the decade  
162 centred on 2070-2080) were used for Representative Concentration Pathway (RCP) 4.5,

163 representing projected climate across NSW in 50 years under a moderate emissions scenario  
164 (Thomson et al., 2011).

#### 165 Species climate niches

166 Realised climate niches were defined for each species within the floristic plot data by  
167 combining with locations of occurrences in the Atlas of Living Australia (ALA; Belbin et al.,  
168 2021). ALA records were cleaned by excluding all but herbarium specimen records, records  
169 prior to 1970, duplicates, records with spatial issues, and records from external territories. ALA  
170 data was extracted and manipulated using the ‘galah’ package (Westgate et al., 2025), and taxa  
171 were aligned to APC names and species not native anywhere in Australia were removed using  
172 ‘APCalign’ (Wenk et al., 2024a). Spatial coordinates of the remaining 2,035,172 records were  
173 matched with the AGCD (Australian Bureau of Meteorology, 2019) to extract data on climate  
174 conditions (MAT, MAP) across the species range (i.e., ‘climate niches’) for each species. We  
175 followed previous calculations of climate niches which used the 2nd and 98th percentiles of  
176 records to represent upper and lower climatic tolerances (Gallagher et al., 2019; Esperon-  
177 Rodriguez et al., 2022)(Figure 1bii).

#### 178 Calculating functional decay

179 Functional decay is calculated from the reduction of FD, as a result of filtering out species  
180 according to future climate projections. The FD of each floristic plot was measured using  
181 multidimensional hypervolumes, a common method in ecology to quantify niche space and  
182 functional trait space of plant communities (Blonder, 2018). Hypervolumes were constructed  
183 for each of the 32,996 floristics plots using original species lists and the six traits mentioned  
184 above. To simulate the effect of species loss from communities as a function of their realised  
185 climate niche limits under climate change, a second set of hypervolumes were constructed  
186 using a subset of species from each plot, filtering out species if the projected MAT and MAP  
187 of a plot location in 50 years under RCP 4.5 is expected to be outside of a species’ current

188 climate niche limits. For each pair of baseline and climate-filtered hypervolumes calculated for  
189 each floristic plot, the proportion of overlapping trait space was calculated to define the relative  
190 loss in functional trait space due to climate filtering (Figure 1c). In plots where changes in  
191 climate are projected to be minor, and/or where the species present have wide climate niches,  
192 fewer species are filtered, and the proportion of hypervolume overlap relative to the baseline  
193 hypervolume will be higher, meaning low functional decay. In cases where places are forecast  
194 to undergo major changes in climate that will exceed the present species' climate niches, more  
195 species will be filtered. If these filtered species represent unique or extreme parts of the  
196 community's trait space, then functional decay will be high, as defined by the much-reduced  
197 overlap between the baseline and climate-filtered hypervolumes.

198 To test the effect of climate change induced losses in FD relative to losses in species richness,  
199 the above protocol was replicated by randomly removing species from hypervolumes instead  
200 of selectively by climate niche. At each floristic plot, the same number of species were removed  
201 as defined in the structured climate niche removal, producing a hypervolume for each floristic  
202 plot with the same number of species as the climate reduced hypervolumes, that could be  
203 overlapped with the original hypervolumes. This procedure provided a form of null expectation  
204 of the effect of species loss for comparison.

205 All calculations of hypervolume overlaps were performed using the *dynRB* package (Junker et  
206 al., 2016). Since hypervolumes can't be calculated with fewer observations (species) than  
207 dimensions (traits), we performed a PCA on the six plant traits to reduce dimensionality to the  
208 first three principal components which captured 73% of variation. This method had little effect  
209 when compared with hypervolumes constructed with all six traits, but allowed more plots  
210 included ( $n = 32,996$ ), and improved accuracy of overlaps from geometric scaling inherent to  
211 hypervolume approaches at higher dimensionality (Mammola, 2019) (S1). To calculate relative  
212 functional decay (i.e. functional decay relative to the proportion of species richness lost from

213 climate filtering), the proportion of FD decline from climate filtering was divided by the  
214 proportion of species richness lost from the same filtering. Resulting values close to one  
215 represent where the proportion of species being removed from a plot translates to a similar  
216 proportion of reduction in the functional hypervolume. Values are bound at zero, where there  
217 hypervolumes do not decay from species removal due to either no species being vulnerable to  
218 climate changes in their present location or functional redundancy with the species being  
219 dropped. High values occur where the species being lost contribute disproportionately to FD,  
220 for example, a relative FD loss of two would mean that the proportion of species being lost  
221 results in twice as much functional decay.

## 222 Statistical Analyses

223 To examine the relationship between reductions in species richness and hypervolume overlap  
224 between baseline and climate-subset species lists, we fit generalized additive models (GAMs)  
225 using the *mgcv* package (Wood, 2017). The analysis included both growth form (woody or  
226 non-woody) and scenario (structured loss via climate margins or random loss) as explanatory  
227 factors. We compared two models: one with a single smooth term for loss of hypervolume  
228 overlap shared across scenarios and growth forms, and another that included separate smooths  
229 for each scenario and growth form combination, allowing the shape of the decline to differ  
230 between groups. Model improvement was evaluated using an F-test, comparing the two models  
231 to determine whether structured and random species removals exhibited significantly different  
232 trajectories of functional decay. All models were fitted using restricted maximum likelihood.  
233 To quantify overall magnitude differences between scenarios, we estimated marginal means  
234 from the full model using the *emmeans* package (Lenth & Piaskowski, 2025), providing  
235 average differences in overlap between structured and random removals for each growth form.  
236 We compared two models: one with a single smooth term for species loss and a parametric  
237 effect of growth form (woody vs non-woody), and another that included separate smooth terms

238 for each growth form to allow the shape of the relationship to differ between groups. All data  
239 manipulation, visualisation, analysis, and mapping were done using R in the integrated  
240 development environment R Studio (R Core Team, 2025). Data and code used in this analysis  
241 can be accessed online here: <https://figshare.com/s/d071cf38009f34856090>.

## 242 **Results**

243 Future climate projections for floristics plots indicate, on average, 2.37°C ( $\sigma = 0.79$ ) of  
244 warming in MAT and a decrease in MAP by 234.8 mm ( $\sigma = 143.9$ ) by 2075 (Figure 2). The  
245 median percentage of species removed from plots due to local climates moving beyond species  
246 present day climate niches was 35.5%, although this varied greatly across the plots examined  
247 (interquartile range [IQR] = 37.2%; S2). Functional decay associated with this species loss was  
248 relatively lower, with the plot median being a 9.5% reduction (IQR = 11.7%) in hypervolume  
249 after species removal. If only woody species are considered, slightly higher proportion of  
250 species were removed (median = 36.5%; IQR = 38.9%) but resulted in much higher reductions  
251 in functional trait space (median = 17.1%; IQR = 28.2%). In contrast, non-woody species  
252 experienced the same loss in species (median = 37.9%; IQR = 39.5%) but retained higher  
253 overlaps in hypervolume space (median = 11.9%; IQR = 20.3%).

254 Results of the GAMs reveal evidence that structured losses of species based on climate niches  
255 reduces FD faster than random species loss (Figure 2). Structured removal of species resulted  
256 in an additional 1.56% loss in hypervolume overlap compared to random species removal  
257 (Table 1). When comparing growth forms, woody communities exhibited the greatest declines  
258 in FD overlap, showing a 10.2% lower overlap than declines when all species are used,  
259 compared with the non-woody subset which was 4.2% lower. Finally, significant positive  
260 interaction terms suggest that subsets of specific growth forms slightly moderate the negative  
261 impact of structured loss. Smooth terms from the GAM further demonstrated strong nonlinear

262 relationships between proportional species loss and hypervolume overlap, with distinct decay  
263 trajectories across growth forms. Woody and non-woody subsets showed distinct patterns of  
264 functional decay ( $p < 0.001$ ). Together, these results provide evidence that climate-induced  
265 structural filtering accelerates functional decay, and that growth form can modulate the shapes  
266 the trajectory of these reductions.

267 Across NSW, most areas are projected to experience slower declines in FD than in species  
268 richness (Figure 4). Median relative FD loss was 0.34 across all plots, meaning that for every  
269 1% loss in species richness, FD is expected to decline by roughly one-third as much (S2). When  
270 separated by growth form, woody species exhibited a higher median relative loss (0.54) than  
271 non-woody species (0.37), meaning that woody species contribute more to plant community's  
272 functional trait space and/or are at greater risk of changing climates. Woody FD appears at  
273 greatest risk of loss, relative to species loss along the Great Dividing Range and western slopes  
274 of NSW, and in the southwestern arid zone.

275 A similar pattern of slower functional decay relative to species richness was also observed  
276 across vegetation types (Table 2). All vegetation types had values below 1, with the highest  
277 being alpine vegetation (0.509), suggesting that the rate of functional decay will be just over  
278 half that of the projected decay of species richness. In contrast, wet sclerophyll forests showed  
279 the lowest relative loss (0.304 for grassy and 0.311 for shrubby types), indicative of higher  
280 functional redundancy. When considering growth forms separately, woody species in wooded  
281 communities (woodlands and dry and wet forests) had greater relative functional decay than  
282 non-woody species in the same communities. The opposite pattern was observed in vegetation  
283 types not dominated by woody vegetation (grasslands and chenopod shrublands), where non-  
284 woody species exhibited greater relative functional decay.

## 285 Discussion

286 Predicting the risk of FD decline in vegetation communities offers a potential guide for  
287 prioritising conservation under climate change. While functional redundancy remains a key  
288 mechanism to slow the decline in FD of plant communities, we show that calculating functional  
289 decay can reveal areas of vulnerability, when patterns of functional decay are decoupled  
290 regarding growth form or vary spatially. By quantifying where and which plant types are at  
291 risk of rapid FD decline, our framework allows conservation practitioners more resolution to  
292 prescribe interventions and identify areas of high climate risk. For example, these insights can  
293 inform proactive restoration strategies, such as the pre-emptive planting of slower maturing  
294 woody species in anticipation of future stress on these species, ensuring that the structural and  
295 functional membership of these ecosystems is maintained as climate-sensitive species decline  
296 in abundance (Di Sacco et al., 2021).

297 When designing strategies that account for functional decay, practitioners need to be strategic  
298 with prioritising species with unique trait combinations that are not predicted to become climate  
299 displaced in the future, but it will also be important to simultaneously protect for high  
300 functional redundancy. Due to the inherent uncertainty in climate models and predictions of  
301 species persistence, it is risky to manage for communities with only the minimum trait diversity  
302 preserved. Instead, restoring for redundancy acts as a critical insurance policy to maximise FD  
303 despite possible additional species loss. Measuring and maintaining areas with high functional  
304 redundancy will also be of vital importance for providing a buffer against rapid declines of FD  
305 and collapse of ecosystem processes as climate change affects community membership (Biggs  
306 et al., 2020).

307 Functional redundancy is a critical biological insurance policy that protects ecosystem stability  
308 by filling ecological niches with species that perform similar roles (Lawton & Brown, 1994).  
309 When species are at risk of being lost due to changing growing conditions, high redundancy

310 allows the community to maintain its overall functionality because remaining species fulfill  
311 similar ecological niches that fill the gap of missing species (Fonseca & Ganade, 2001). This  
312 mechanism explains the observed and predicted decoupling of species richness loss and FD  
313 loss seen in this study as well as other Australian (Gallagher et al., 2013) and European  
314 (Thuiller et al., 2006) plant communities under future climate scenarios. However, the  
315 protection offered by redundancy is finite and depends heavily on the distribution of traits  
316 within the community (Reich et al., 2012). While functional redundancy can be greater with  
317 more species in a community, the extent and potential loss of FD, as measured using the  
318 hypervolume approach, is defined by the extreme trait values (Blonder, 2018). This means that  
319 safeguarding FD from changes in community composition should aim to retain the species with  
320 extreme trait values that contribute disproportionately to functional trait space and whose loss  
321 would result in the greatest changes in the functional properties of the community. By  
322 combining broad functional redundancy with the targeted protection of these extreme trait  
323 values, conservation managers can hedge against predictive uncertainty and ensure vital  
324 ecological niches remain filled.

325 Measuring the risk of FD loss from climate change provides a more mechanistic understanding  
326 of ecosystem vulnerability and offers specific insights that can better shape conservation and  
327 restoration priorities. Our finding that woody communities are more vulnerable to functional  
328 decay is particularly concerning given the life histories and adaptive capacities of these species.  
329 Since these woody species generally have longer generation times and slower growth rates  
330 (Petit & Hampe, 2006), their capacity for *in situ* adaptation as well as dispersal speed is lower  
331 than species that are faster to grow and reproduce (Corlett & Westcott, 2013). Consequently,  
332 there is a heightened likelihood of local extinctions when the rate of climatic shift is expected  
333 to exceed the current distributions of woody species. With climate risk of plant communities  
334 being biased toward a particular suite of species that contribute a distinct and important part of

335 trait space to FD, conservation interventions may be needed to prevent decline (Nicoitra et al.,  
336 2015).

337 One method for stemming the decline in FD would be to prioritise species with unique trait  
338 combinations that are vulnerable to decline in restoration efforts using climate-adjusted  
339 provenancing. This strategy involves strategically selecting genetic material for restoration  
340 from regions with growing conditions more similar to conditions projected in the future, as  
341 opposed to local provenancing which prioritises source material that is locally adapted to  
342 current growing conditions (Prober et al., 2015). This method bypasses some of the limitations  
343 of natural dispersal and adaptation, expediting the resilience of communities to novel climates  
344 (Di Sacco et al., 2021). Strategic selection of species and provenancing, can also reinforce  
345 resilience to disturbances that may be exacerbated by climate change by restoring traits that are  
346 robust to specific threats such as fire resprouting capacity or drought tolerance (Laughlin et al.,  
347 2017). Further, proactively planting species that contribute disproportionately to community  
348 FD that are also at the greatest risk of decline from changing growing conditions could help  
349 safeguard FD under climate change. In the case of woody species, which represent a suite of  
350 species at greater risk of climate induced reductions of FD, pre-emptive planting may buy time  
351 for slow to adapt species, while also slowing down FD decline. However, implementing these  
352 proactive strategies at scale faces significant practical hurdles, primarily, the availability and  
353 supply of seeds from diverse, climate-ready provenances remains a critical bottleneck for  
354 restoration practitioners (Andres et al., 2024). Addressing these supply-chain issues will be  
355 another essential challenge for successfully safeguarding the FD of ecosystems into the future.

356 Due to the uncertainty, and variability in how areas will experience climate changes, it is likely  
357 that the effect on plant persistence and growing conditions will also vary greatly. This means  
358 that while local extinctions are already widespread and predicted to continue (Wiens, 2016),  
359 many species will first experience declines in abundance, fitness, and recruitment as conditions

360 shift away from a species' physiological optimum (Condit et al., 1996; Huang et al., 2025).  
361 Since the hypervolume approach utilised in this study is not weighted by abundance, the  
362 implications of these "declining but persisting" species may be overstated in terms of absolute  
363 trait space loss. However, even if species persist in lower densities, their reduced abundance  
364 will drive their functional contributions to ecosystem processes (Winfree et al., 2015),  
365 suggesting that our results still correctly identify the species most likely to contribute to  
366 functional decay.

367 The future trajectory of FD of plant communities will also be shaped by the colonisation of  
368 new species. Modelling species gain from climate induced community turnover adds additional  
369 levels of complexity because it requires accounting for varying dispersal capacities (Garcia et  
370 al., 2014) and the overcoming of biotic resistance from the resident community (Urban et al.,  
371 2012). Due to the lack of data on dispersal capacity for species at large scales as well as the  
372 highly stochastic and dynamic nature of species-specific interactions, modelling novel species  
373 under future scenarios can introduce considerable uncertainty. While there is already some  
374 work to predict climate induced range shifts in plant species (Bradley et al., 2024; Tomiolo &  
375 Ward, 2018), future research that integrates both climate filtering and dispersal-constrained  
376 colonisation models would provide a more holistic view of community reassembly. This  
377 approach has the potential to identify where the introduction of novel trait space might  
378 compensate for the decline or accelerate the change in functional membership of the original  
379 community.

380 Predicting potential losses in FD provides a critical macroecological tool for prioritising the  
381 selection of new protected areas. Many mechanisms exist to expand protected area networks,  
382 including the rapid growth of privately protected areas, offering diverse opportunities to  
383 safeguard biodiversity and improve the representativeness of conservation reserves (Alves-  
384 Pinto et al., 2021; Bingham et al., 2021). By integrating functional decay predictions into

385 selection processes for expanding conservation areas, practitioners have more information to  
386 align investments to conservation priorities. Areas predicted to be highly resilient to climate  
387 induced functional decay, may be desirable for conservation as refugia for FD. These places  
388 would require minimal intervention and act as stable reservoirs of ecosystem processes and  
389 services and provide vital insurance populations that can support broader landscape stability  
390 (Keppel et al., 2012). Alternatively, areas identified as high risk of rapid FD loss may be  
391 eligible of significant proactive intervention to rebuild trait space and maximise redundancy.  
392 Identifying areas of high biodiversity and implementing protection measures is in line with  
393 conservation goals globally (Maxwell et al., 2020). FD represents a dimension of biodiversity  
394 that is being increasingly recognised as a key goal for safeguarding ecosystems and their vital  
395 functions (Pollock et al., 2020; Tobias et al., 2025). Whether used to identify resilient  
396 strongholds or vulnerable biodiversity, the addition of FD metrics offers additional resolution  
397 to inform conservation planning.

398 As climate change continues to reshape global vegetation, broadening our focus to include FD  
399 decline is essential for predicting the future of ecosystem stability. While functional  
400 redundancy offers a vital buffer against rapid loss of FD, our findings reveal patterns of  
401 vulnerability in certain growth forms and habitats. Integrating metrics like functional decay  
402 into conservation and restoration planning provides a more mechanistic lens to identify where  
403 ecosystem stability is most at risk and how this may be remedied. By prioritising the protection  
404 of FD and implementing proactive strategies, practitioners can safeguard the essential  
405 ecological processes that sustain biodiversity in a rapidly changing climate.

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#### 411 Declaration of generative AI technologies in the manuscript preparation process

412 During the preparation of this work the authors used Gemini 3.1 Pro for editing text and code.

413 After using this tool, the authors reviewed and edited the content as needed and take full

414 responsibility for the content of the published article.

415

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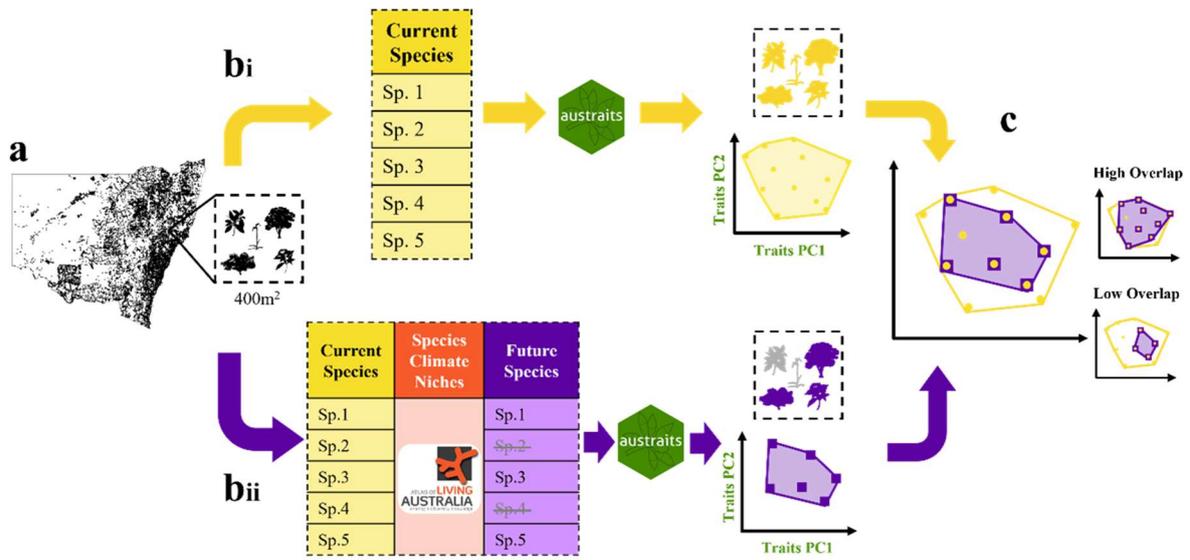
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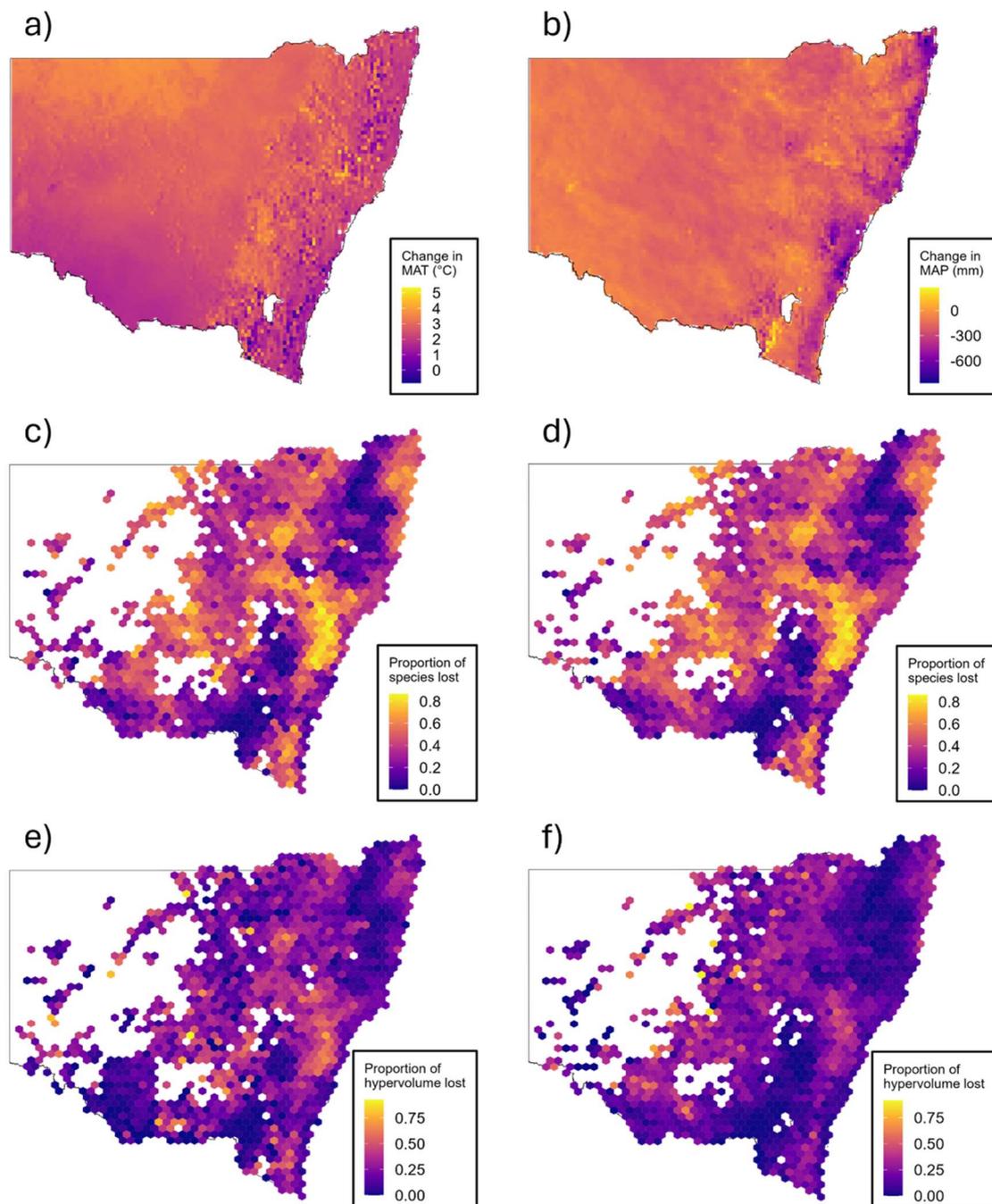
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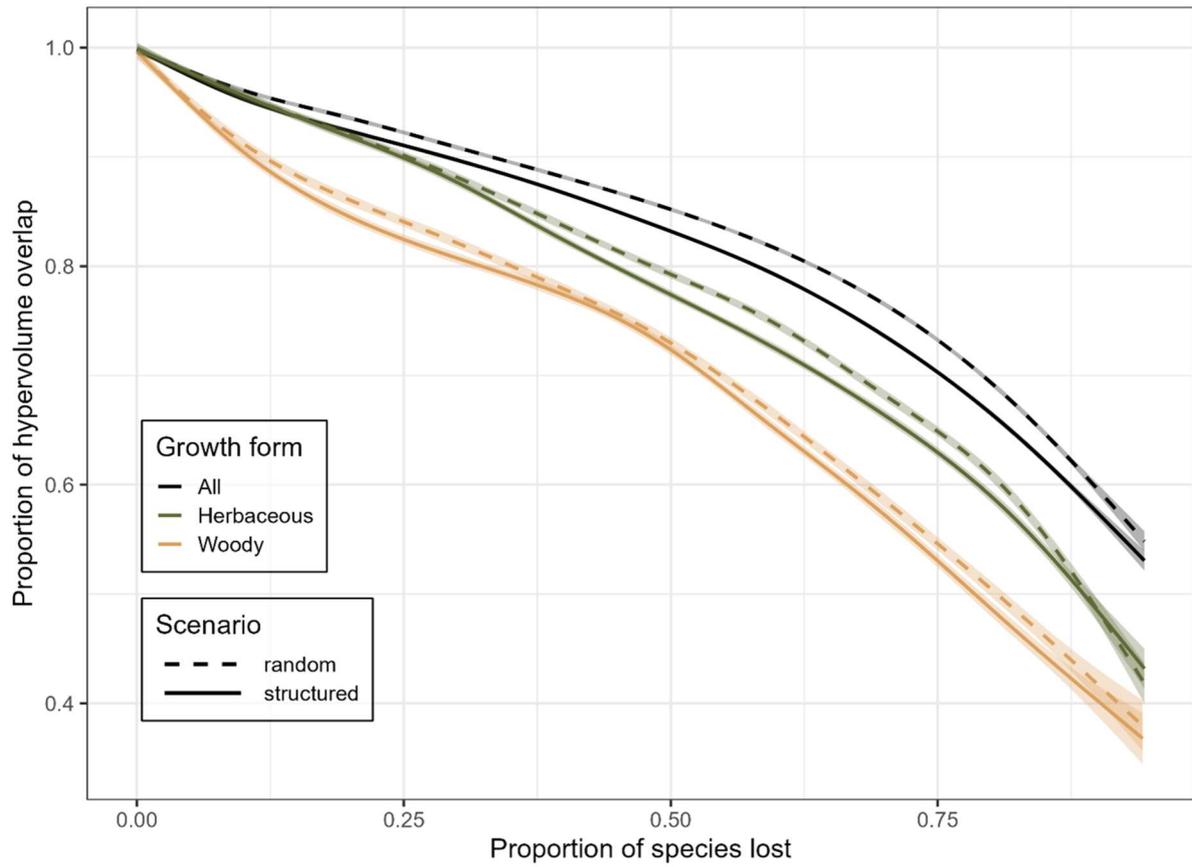
722 Figure 1. (a) Species lists from 32,996 floristic survey plots were (bi) joined with gap-filled trait  
 723 information from AusTraits (plant height, leaf area, leaf mass per area, leaf nitrogen per dry mass,  
 724 seed mass, and stem density; Falster et al., 2021) to calculate hypervolumes for each survey plot. (bii)  
 725 Future hypervolumes were created by defining climate niches for each species based on their current  
 726 extents of occurrence from the Atlas of living Australia (Belbin et al., 2021) and filtered out of plot  
 727 level lists if a species is not expected to remain within its current climate niche in 2075 under a  
 728 climate change scenario of RCP 4.5. (c) The proportion of overlap of current and future hypervolumes  
 729 was measured for each floristics plot using all species, and again separately for woody, and non-  
 730 woody species.

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732

733 Figure 2. Maps of change in New South Wales between current and 2075 climate under RCP4.5.  
 734 Maps (a) and (b) respectively show forecasted change in mean annual temperature at sea level and  
 735 change in mean annual precipitation based on NARClIM 2.0 (Di Virgilio et al., 2025). Map (c) shows  
 736 the proportion of woody species, and (d) non-woody species that have been removed from each  
 737 floristics plot based on species climate niches relative to each plot's future climate. Maps (e) and (f)  
 738 show the proportions of woody and non-woody community hypervolume lost (functional decay) from  
 739 the same species removal. Maps C-F display values for each floristics plot aggregated into hexbins  
 740 and coloured by mean values.

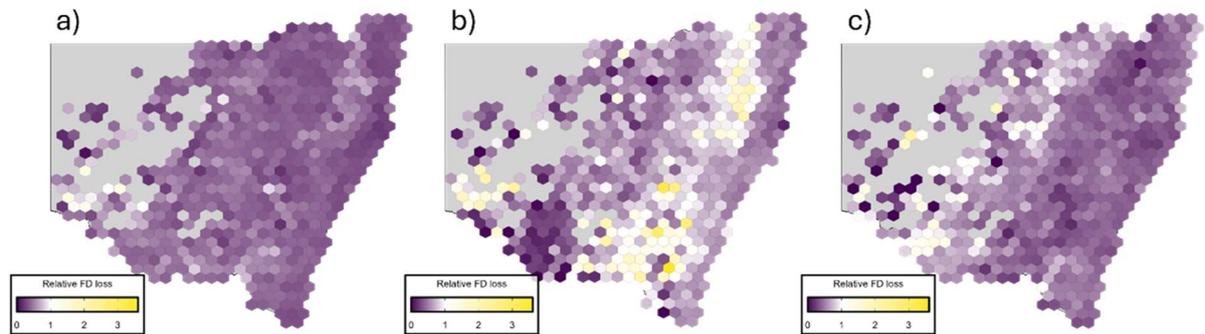


741

742 Figure 3. Decline in plot level functional diversity from hypervolume overlaps resulting from species  
 743 removal based on 2073 RCP4.5 climate projections for plot locations relative to species' current  
 744 climate niches. Curves represent smoothed trends from generalised additive models (GAMs) for  
 745 32,996 plots for all species (black), only woody species (brown), and only non-woody species (green).  
 746 Models were fit for reductions in hypervolumes via structured removal of species based on their  
 747 climate niches (solid), and separately via random species loss (dashed). Ribbons represent 95%  
 748 confidence intervals.

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750



751

752 Figure 2. Maps of proportion of functional diversity decline relative to proportion of species decline  
753 after climate filtering. Values of one represent areas where the proportion of species removed due to  
754 projected climate conditions in 2075 translates to the same proportion of functional decay in the  
755 original hypervolume. Values close to zero represent areas with high functional redundancy that are  
756 protected from rapid functional decay when species are lost. Values above one are areas where the  
757 rate of functional decay outpaces the rate of species decay, i.e. a value of two means that for each  
758 proportion of species removed from climate filtering, two times as much functional trait space is lost.  
759 Maps are produced for the relative decay of all species (a), only woody species (b), and only non-  
760 woody species (c). Relative functional diversity loss values for all 32,996 plots have been aggregated  
761 using the mean values of each hexbin.

762

## 763 Tables

764 Table 1. Summary of parametric terms for the Generalized Additive Model (GAM) of hypervolume  
 765 overlap after structured and random removal of species from functional trait space. Estimates  
 766 represent the linear offsets for decline scenarios (random/structured by climate niche) and growth  
 767 forms (all species, woody only, and non-woody only) relative to baseline (random/all species).

Parameters	Estimate	St. error	t-statistic	p-value
Intercept	0.875	0.0007	1300.284	<0.001
Structured decline	-0.016	0.001	-16.424	<0.001
Non-woody only	-0.041	0.001	-42.964	<0.001
Woody only	-0.102	0.001	-104.023	<0.001
Structured:non-woody interaction	0.005	0.0014	4.003	<0.001
Structured:woody interaction	0.006	0.0014	4.097	<0.001

768

769 Table 2. Median and interquartile ranges (IQR) of the relative functional decay (proportion of  
 770 functional diversity decline relative to proportion of species decline after climate filtering) for  
 771 vegetation formations across New South Wales. Vegetation classification from (Department of  
 772 Planning and Environment, 2017). Relative functional diversity loss values for each formation are  
 773 presented for all species, only woody species, and non-woody species.

Vegetation Formation	median (all species)	IQR (all species)	median (woody)	IQR (woody)	median (non- woody)	IQR (non- woody)	n plots
Alpine complex	0.509	0.411	2.184	2.914	0.281	0.346	21
Arid shrublands (Acacia)	0.357	0.254	0.460	0.388	0.558	0.519	237
Arid shrublands (Chenopod)	0.377	0.301	0.055	0.411	0.557	0.648	427
Dry sclerophyll forests (Grassy)	0.328	0.204	0.646	0.562	0.290	0.292	4379
Dry sclerophyll forests (Shrubby)	0.341	0.200	0.560	0.436	0.358	0.365	7356
Forested wetlands	0.359	0.225	0.379	0.760	0.441	0.389	1760
Freshwater wetlands	0.372	0.259	0.506	0.852	0.422	0.402	1289
Grasslands	0.405	0.248	0.030	0.847	0.475	0.349	1235
Grassy woodlands	0.365	0.233	0.751	0.847	0.326	0.314	5629
Heathlands	0.308	0.175	0.461	0.428	0.378	0.473	1046
Rainforests	0.321	0.200	0.436	0.361	0.409	0.445	1471
Saline wetlands	0.416	0.242	0.103	0.541	0.585	0.540	214
Semi-arid woodlands (Grassy)	0.377	0.268	0.423	0.546	0.569	0.574	1246
Semi-arid woodlands (Shrubby)	0.406	0.243	0.558	0.524	0.500	0.456	1376
Wet sclerophyll forests (Grassy)	0.304	0.213	0.481	0.464	0.297	0.317	2297
Wet sclerophyll forests (Shrubby)	0.311	0.204	0.480	0.398	0.352	0.331	2335

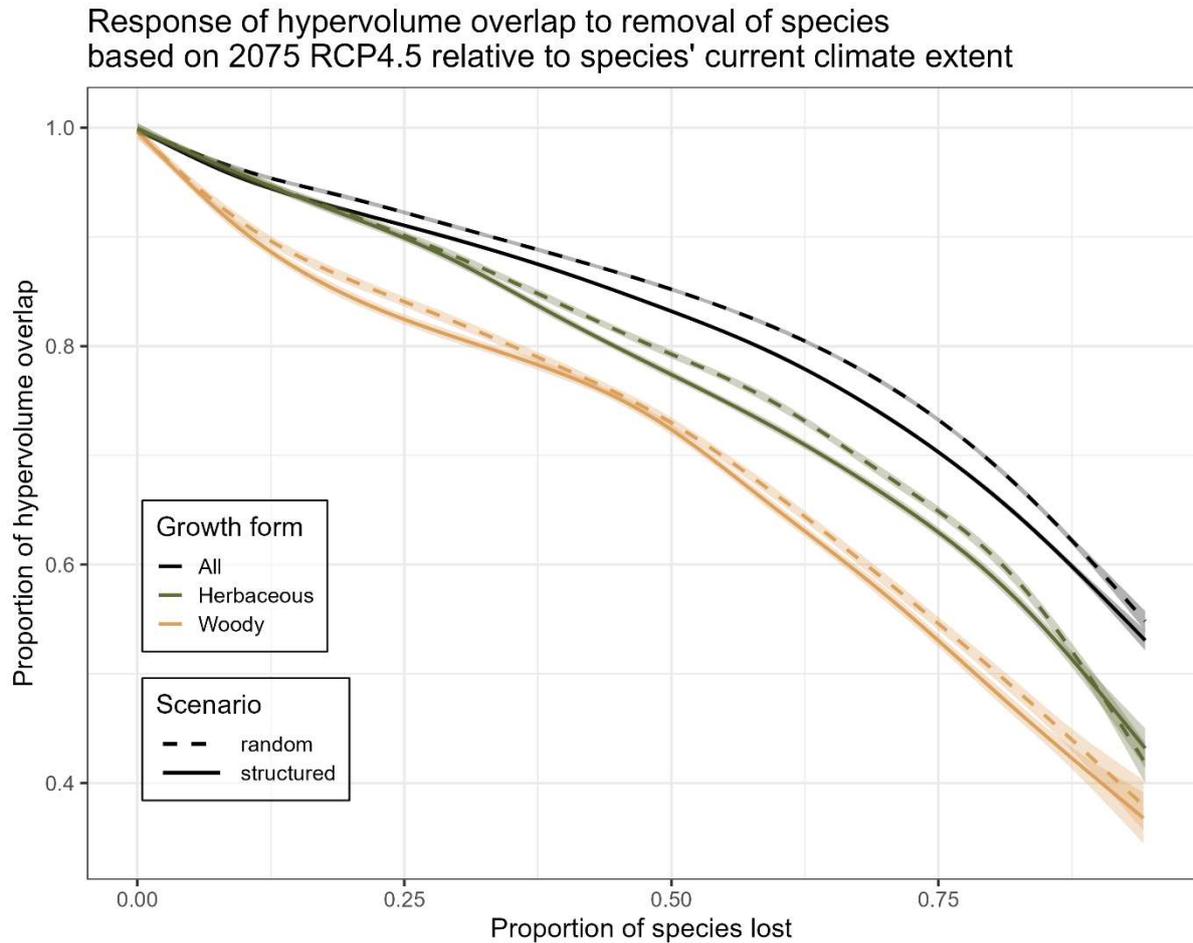
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776 Supplementary material for: *Predicting decay in functional diversity in plant communities*  
777 *under future climates*

778

779 **S1** Comparison of results from decline in hypervolume overlap from species removal  
780 between raw traits (leaf area, leaf mass per area, leaf nitrogen content, plant height, seed  
781 mass, and stem density) and the first three principal components of a PCA of these traits.

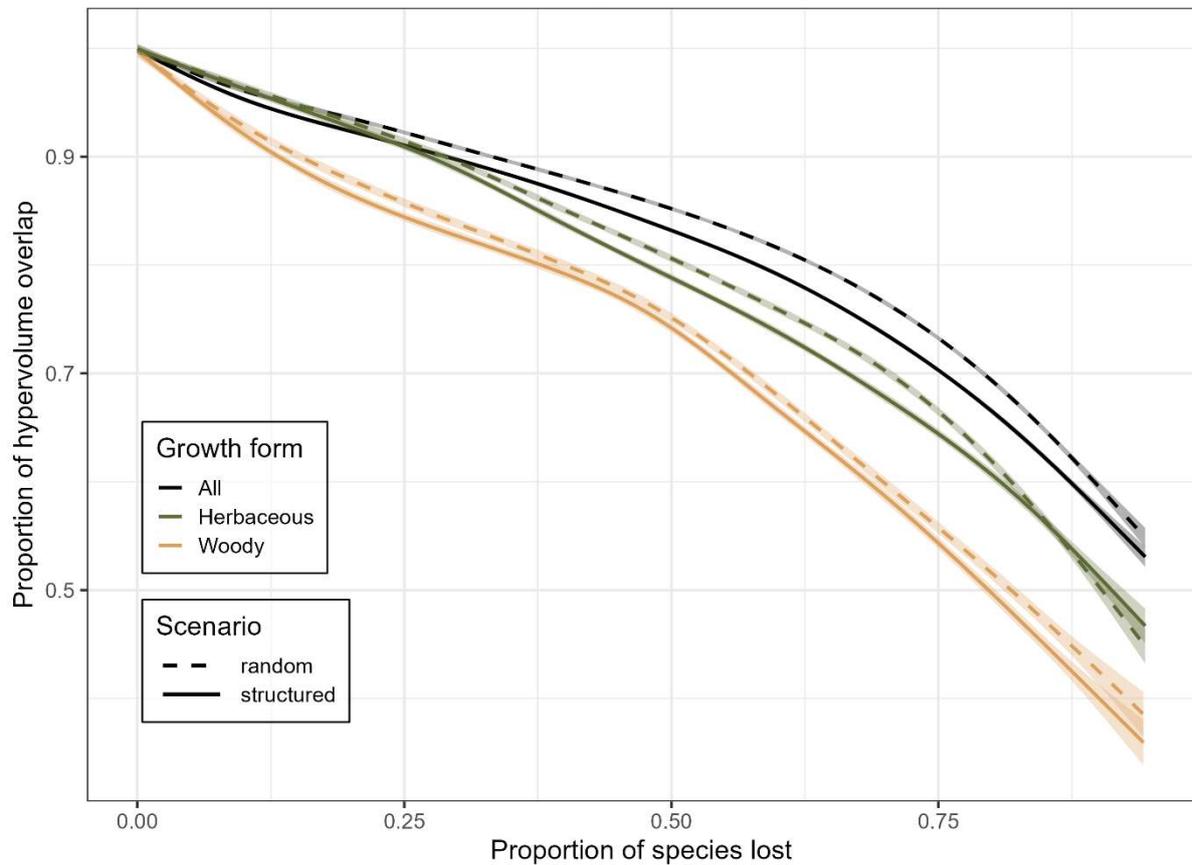


782

783 Figure 1. Figure 3 from main paper. Decline in plot level functional diversity from hypervolume  
784 overlaps resulting from species removal using first three principal components of six functional traits.

785

Response of hypervolume overlap to removal of species based on 2075 RCP4.5 relative to species' current climate extent



786

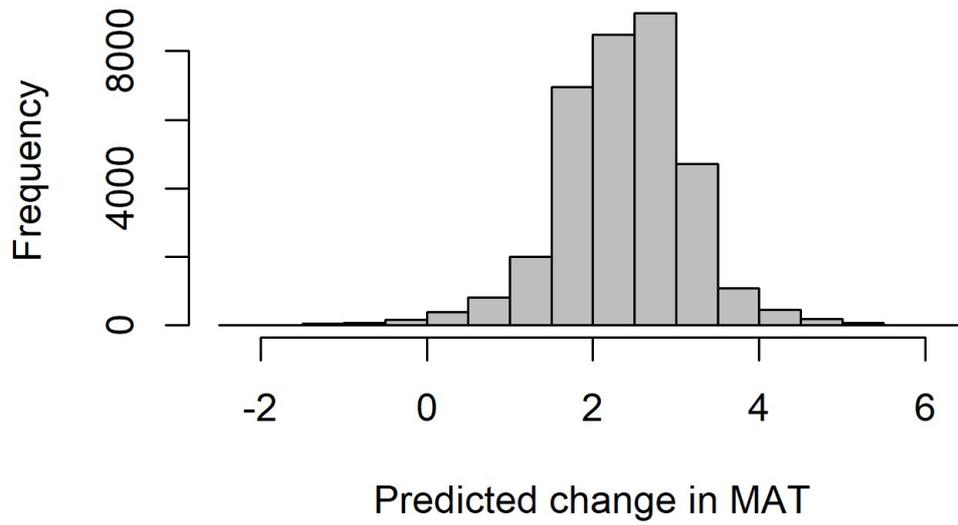
787 Figure 2. Decline in plot level functional diversity from hypervolume overlaps resulting from species  
788 removal using all six log transformed trait values without reduction via PCA. This method excludes  
789 vegetation surveys with fewer than seven species present since the number of observations for  
790 calculating a hypervolume must be greater than the number of dimensions.

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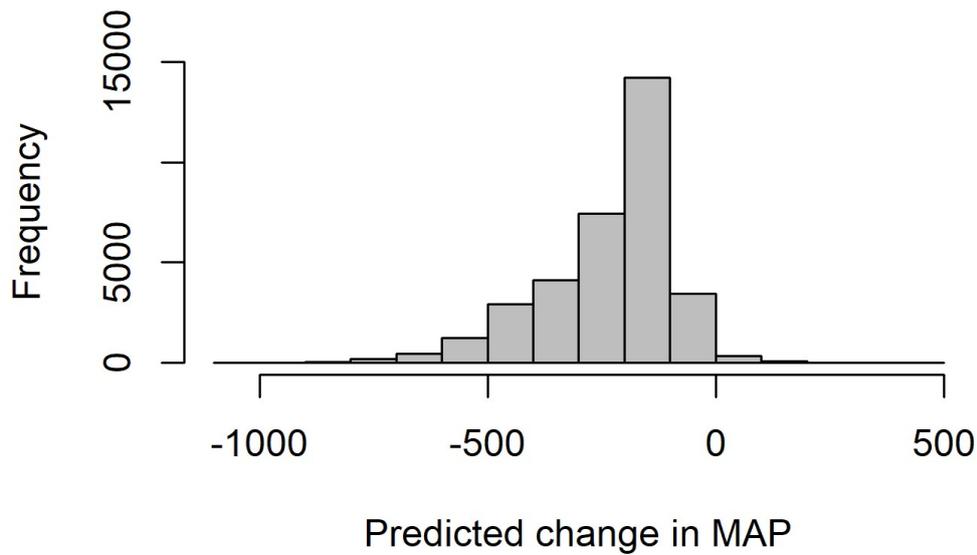
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794 **S2** Histograms of floristic plot network's projected climate change, change-induced number  
795 of species removed, and subsequent functional diversity decline.



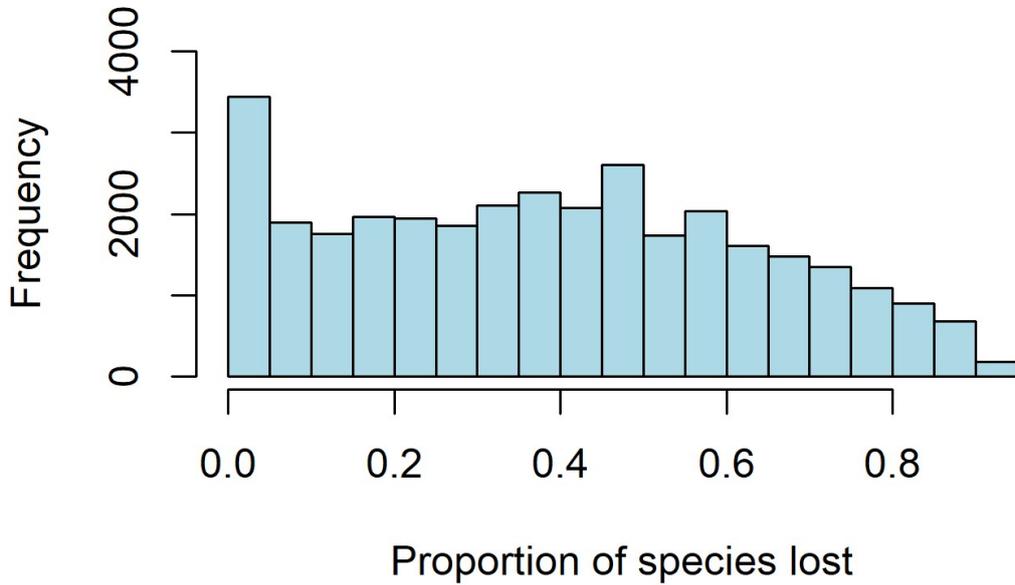
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797 Figure 3. Projected change in mean annual temperature for each plot according to NARClIM 2.0 (Di  
798 Virgilio et al., 2025).



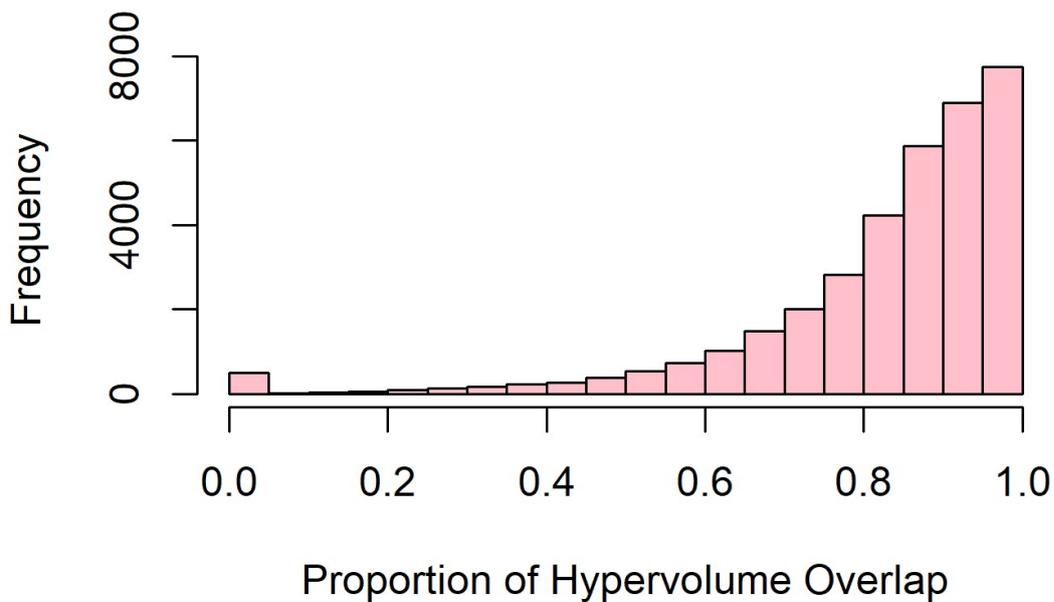
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800 Figure 4. Projected change in mean annual precipitation for each plot according to NARClIM 2.0 (Di  
801 Virgilio et al., 2025).



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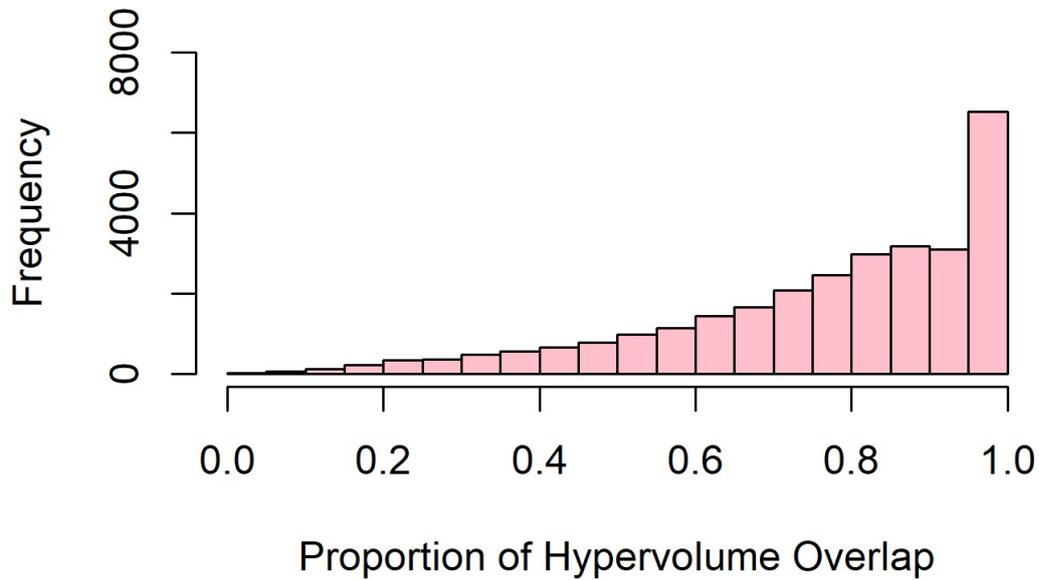
804 Figure 5. Proportion of species removed at each floristics plot after filtering by species climate niche  
 805 relative to projected climate at that plot location.



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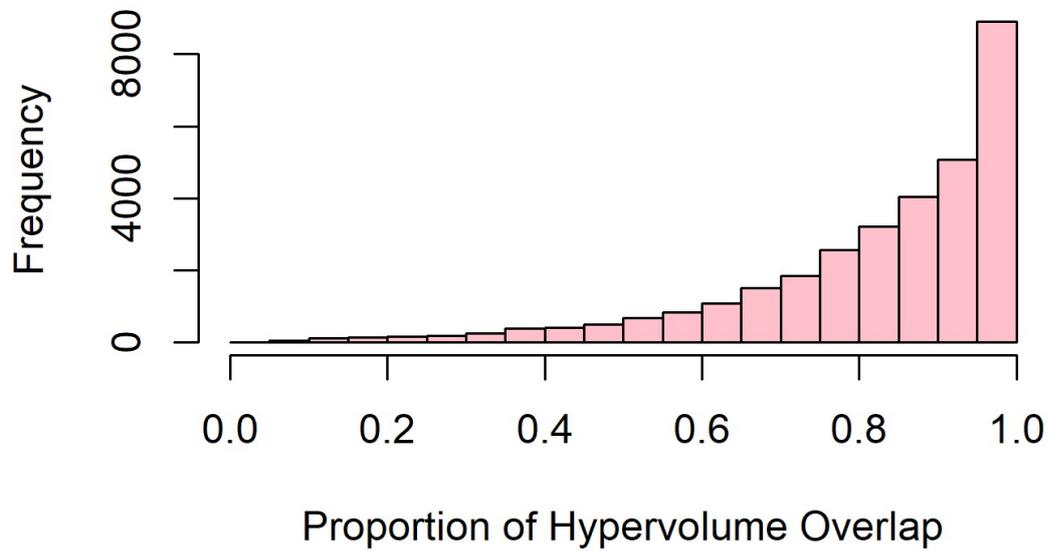
807 Figure 6. Proportion of overlap between the new climate-filtered trait space hypervolume, and original  
 808 hypervolume for each floristics plot using all species. Values of 1 represent plots that retain full

809 overlap and therefore lose no functional diversity after removal of species that will no longer be  
810 within their current climate niches. Values of 0 represent plots which will have all species removed  
811 from the climate filtering process and therefore lose all functional diversity.



812

813 Figure 7. Proportion of overlap between the new climate-filtered trait space hypervolume, and original  
814 hypervolume for each floristics plot using woody species only. Values of 1 represent plots that retain  
815 full overlap and therefore lose no functional diversity after removal of species that will no longer be  
816 within their current climate niches. Values of 0 represent plots which will have all species removed  
817 from the climate filtering process and therefore lose all functional diversity.



818

819 Figure 8. Proportion of overlap between the new climate-filtered trait space hypervolume, and original  
 820 hypervolume for each floristics plot using non-woody species only. Values of 1 represent plots that  
 821 retain full overlap and therefore lose no functional diversity after removal of species that will no  
 822 longer be within their current climate niches. Values of 0 represent plots which will have all species  
 823 removed from the climate filtering process and therefore lose all functional diversity.

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