

1 **Plasticity drives geographic variation and trait coordination in blue oak drought**
2 **physiology**

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19 **Abstract**

20
21 Two decades of widespread drought-induced forest mortality events on every forested continent
22 have raised the specter of future unpredictable, rapid ecosystem changes in 21st century forests.
23 Yet our ability to predict drought stress, much less drought-induced mortality across the
24 landscape remains limited. This uncertainty stems at least in part from an incomplete
25 understanding of within-species variation in hydraulic physiology, which reflects the interaction
26 of genetic differentiation among populations (ecotypic variation) and phenotypic plasticity in
27 response to growth environment. We examined among-population genetic differentiation in a
28 number of morphological and hydraulic traits in California blue oak (*Quercus douglasii*) using a
29 30 year old common garden. We then compared this genetic trait differentiation and trait-trait
30 integration to wild phenotypes in the field from the original source populations.

31 We found remarkably limited among-population genetic differentiation in all traits in the
32 common garden, but considerable site-to-site variation in the field. However, it was difficult to
33 explain trait variation in the field using site climate variables, suggesting that gridded climate
34 data does not capture the drivers of plasticity in drought physiology in this species. Trait-trait
35 relationships were also considerably stronger in the field than in the garden, particularly links
36 between leaf morphology, leaf hydraulic efficiency and stem hydraulic efficiency. Indeed, while
37 twelve of 45 potential trait-trait relationships showed significant wild phenotypic correlations,
38 only four relationships showed both genetic and phenotypic correlations, and five relationships
39 showed significantly different genetic and phenotypic correlations. Collectively, our results
40 demonstrate limited ecotypic variation in drought-related physiology but considerable
41 geographic variation in physiology and phenotypic integration in the wild, both driven largely by
42 plasticity.

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47 **Introduction:**

48 In the 21st century, trees living in a hotter, more variable and often drier world will need
49 to acclimate or adapt to avoid local extirpation, or shift their geographic ranges through multi-
50 generational migration. Recent drought- or heat-induced forest mortality events highlight the
51 vulnerability of even highly drought-adapted forests to climate change (Allen *et al.* 2010;
52 Brodribb *et al.* 2020; Hammond *et al.* 2022). Mass tree die-offs also illustrate the potential for
53 extremely rapid ecosystem changes in a warming world, which have profound ecological
54 consequences and impacts on human society (Anderegg *et al.* 2012). Unfortunately, despite
55 multiple decades of concerted effort to understand the causes of drought-induced forest
56 mortality, we still struggle to predict when and where trees will die off during drought (Trugman
57 *et al.* 2021).

58 Part of the large uncertainty about drought vulnerability is a poor understanding of
59 physiological variation within species (Trugman *et al.* 2021). Within-species variation can be
60 substantial (Martinez-Vilalta *et al.* 2009; Mclean *et al.* 2014; Anderegg *et al.* 2021), can decrease
61 climate vulnerability in some populations (Laforest-Lapointe *et al.* 2014; Garcia-Forner *et al.*
62 2016), and can differ between co-occurring species (Anderegg & HilleRisLambers 2016).
63 Drought resistance is the complex result of numerous plant traits, all of which potentially vary
64 across populations within a species. A key drought tolerance trait, namely xylem resistance to
65 embolism, often shows limited among-population variation in conifers (Lamy *et al.* 2013) and
66 angiosperms (Skelton *et al.* 2019). But morphological characteristics, for example high leaf mass
67 per area (LMA) and high leaf dry matter content (LDMC) may indirectly allow plants to
68 maintain function under increasingly negative water potentials during drought (Lamont *et al.*
69 2002; Poorter *et al.* 2009; Bartlett *et al.* 2012). Meanwhile, shifting allocation to different tissues,
70 for example decreasing leaf area to sapwood area ratio (AL:AS), and increasing tissue-specific
71 hydraulic efficiency can help plants avoid drought stress by minimizing the water potential drop
72 required to maintain transpirational flux (Gleason *et al.* 2013; Mencuccini *et al.* 2019). Across
73 species, coordinated physiological strategies or trait syndromes lead to correlated variation
74 across many of these traits (Reich *et al.* 2003; Chave *et al.* 2009; Mencuccini *et al.* 2015;
75 Sanchez Martinez *et al.* 2020). However, within individual species, these broad evolutionary
76 trait-trait correlations often break down (Anderegg *et al.* 2018; Messier *et al.* 2018; Rosas *et al.*
77 2019). Consequently, both the total amount of within-species variation in drought resistance-
78 related traits and the key physiologic axes that drive spatial variation in drought resistance
79 remain poorly understood.

80 Possibly more important than the total amount of within-species variation are the drivers
81 of this variation. Intraspecific variation can arise from two distinct processes with drastically
82 different implications for near-term climate responses. First, spatio-temporal variation in
83 environmental selection on heritable fitness-related phenotypes can lead to genetic differentiation
84 among populations and local adaptation of functional traits (traits that mediate plant performance
85 in a given environment) (Alberto *et al.* 2013). Substantial geographic variation in drought
86 physiology due to local adaptation would imply that certain populations or genotypes (and not
87 others) are drought resistant and that gene-flow (assisted or natural) is necessary for other
88 populations to manifest improved drought resistance (Hoffmann *et al.* 2021). Local adaptation is
89 widespread in plants, particularly species with large population sizes (Leimu & Fischer 2008;
90 Savolainen *et al.* 2013). Indeed, provenance trials or common gardens (where multiple
91 populations of a species are planted in a common environment) almost always detect genetic
92 differentiation among populations in trees (Alberto *et al.* 2013; Ramírez-Valiente *et al.* 2022)

93 and landscape genetic/genomic approaches often reveal evidence for local adaptation
94 (Savolainen *et al.* 2013; Capblancq *et al.* 2020; Gugger *et al.* 2021; Dauphin *et al.* 2022).
95 However, 'home site advantage' (a hallmark of local adaptation) has proven rarer than expected
96 (see meta-analyses Leimu & Fischer 2008; Oduor *et al.* 2016), though it is harder to test for, as it
97 requires reciprocal transplant experiments and lifetime fitness estimates.

98 Alternatively, adaptive trait plasticity, or the ability of each genotype to manifest a broad
99 range of phenotypes depending on environmental cues, can generate geographic variation in
100 water stress-related traits independent of genetic variation. If plasticity is not itself locally
101 adapted (i.e., all populations or genotypes have the same amount of plasticity), all populations of
102 a species could manifest drought resistant traits given the right environmental cues. As sessile
103 organisms that experience a range of environments over their lifetime and even in different parts
104 of the same organism (e.g., light availability in different parts of the canopy), plants show
105 marked plasticity in many traits (Poorter *et al.* 2009; Palacio-López *et al.* 2015; Keenan &
106 Niinemets 2016). Indeed, substantial plastic responses to drought and cold stress have been
107 observed in multiple tree species (Gimeno *et al.* 2009; Gárate-Escamilla *et al.* 2019). However,
108 the prevalence of active adaptive plasticity (as opposed to passive plasticity that results from
109 reduced growth or other stresses under environmental limitation) remains the subject of long
110 running debate (van Kleunen & Fischer 2005; Palacio-López *et al.* 2015).

111 Blue oak (*Quercus douglasii* Hook & Arn) is a culturally and ecologically important tree
112 species and the dominant species in many of the oak savannas in California, USA. Blue oak
113 experienced substantial and spatially widespread mortality during a major drought from 2012-
114 2016, particularly in the southern portion of its geographic range (Brown *et al.* 2018;
115 McLaughlin *et al.* 2020). This mortality highlights the potential vulnerability of blue oak in a
116 changing climate, necessitating an improved understanding of blue oak drought tolerance in
117 space and time to support proactive oak management. Blue oak grows across a wide latitude and
118 huge range of water availability, and thus likely exhibits substantial within-species phenotypic
119 variation. While blue oak exhibits minimal within-species variation in its xylem vulnerability to
120 embolism (P50, or the water potential at which xylem suffers 50% embolism, a key drought
121 tolerance metric, Skelton *et al.* 2019), drought avoidance traits such as hydraulic efficiency and
122 allocation to transpiring leaf area as well as additional traits related to drought tolerance, such as
123 leaf robustness (specific leaf area or SLA, leaf dry matter content or LDMC) are expected to
124 vary considerably across blue oak populations.

125 We quantified the extent and drivers of geographic variation in drought-related traits
126 within mature blue oak trees. We asked 1) how much do drought-related traits vary across the
127 landscape, 2) how is drought resistance coordinated across different traits and tissues, and 3)
128 does spatial variation and trait coordination arise from local adaptation or plasticity? We sought
129 to disentangle the relative roles of local adaptation versus plasticity by measuring drought-related
130 traits in a common garden experiment compared to the traits of the source populations in the
131 wild. In the garden, trait differences between populations are indicative of between-population
132 genetic differentiation/local adaptation (assuming limited maternal effects). Meanwhile,
133 differences between the traits measured in the common garden and those measured in the wild
134 source populations are due to plasticity.

135

136 **Methods:**

137 Blue oak (*Quercus douglasii* Hook & Arn.) is a deciduous species, which is endemic to
138 California but widespread and abundant throughout the state in low elevation woodlands around
139 the California Central Valley (Fig. S1). We measured morphological and hydraulic traits of

140 leaves and stems from seven populations of blue oak in the wild and in a ~30 year old,
141 reproductively mature common garden. These populations were selected to span the geographic
142 range and range of moisture availability of *Q. douglasii* (Fig. S1, Table S1), using only
143 populations whose original acorn source (for the common garden) had been accurately relocated,
144 and whose source populations were accessible based on current land tenure. Climate data for the
145 source populations, both 1951-1980 climate normal and 2018 water year meteorology, were
146 extracted from the California state-wide Basin Characterization Model (Flint *et al.* 2013).
147

148 *Common garden sampling*

149 To investigate the amount of among-population genetic trait differentiation, we sampled an
150 existing provenance trial/common garden planted at the Hopland Research and Extension Center
151 (CA, USA). This trial was planted in 1992 with acorns collected from 26 *Q. douglasii*
152 populations across California and planted in a randomized block design (J. McBride, pers.
153 comm.; see also McBride *et al.* 1997). We subsampled seven populations, capturing as much of
154 *Q. douglasii*'s aridity range as possible. For each of the seven populations, we sampled five to
155 six individuals for hydraulic traits, leaf traits and branch wood density. Between April and mid-
156 June of 2018, we collected >1 m long branches from the sunlit, south-facing portion of the
157 canopy in the early morning (before 9am local time), relaxed the xylem by repeatedly recutting
158 the stem underwater, and then placed the branches in large plastic bags for immediate transport
159 back to the lab. One to two individuals from each of the seven sampled populations were
160 collected from the garden at each sampling point (once or twice weekly) to control for temporal
161 variation in hydraulic traits. Three small terminal twigs and subtending leaves were collected at
162 the same time for the measurement of morphological traits. Tree diameter at 50cm and total tree
163 height was also surveyed for every common garden tree in the winter of 2017 and used to
164 calculate the total stem volume of the largest stem (assuming the stem was a cylinder) as a metric
165 of total growth rate since planting.
166

167 *Wild population sampling*

168 We collected branches for trait measurement from six to eight mature trees from the acorn source
169 populations used in the garden. Large branches (typically >1.5m long and >4cm basal diameter)
170 from the south-facing canopy were collected in the same manner as in the common garden. Tree
171 cores were also collected from the sampled trees for calculation of radial growth rates.
172

173 *Morphological Traits*

174 We selected three terminal branches from the south-facing sun-exposed canopy for
175 morphological measurements (Table 1), cut at the prior year bud scar and including all current
176 year stem and leaf tissue. Branches were rehydrated for >12 hrs using the 'partial rehydration'
177 method (Pérez-Harguindeguy *et al.* 2013). We then measured specific leaf area (SLA, cm^2 wet
178 leaf area per g^{-1} leaf dry mass), leaf dry matter content (LDMC, g leaf dry mass per g^{-1} leaf wet
179 mass), median leaf size (cm^2 fresh leaf area), leaf dry mass to stem dry mass ratio ($M_L:M_S$), and
180 leaf area to sapwood area ratio ($A_L:A_S$, cm^2 leaf area per mm^2 stem area underneath bark) on
181 these current year terminal twigs using calipers, balances, and ImageJ image analysis software.
182 We calculated mean leaf size as the average area per leaf for each terminal branch. We also
183 measured wood density (WD, g dry mass per cm^3 wet volume) on one to five branch disks 2-5cm
184 in diameter cut from the basal end of branches collected for hydraulic sampling. Bark was
185 removed from branch disks and wet volume was measured via water displacement on a balance.

186 For all analyses using individual or population average traits, we also included leaf and
187 stem P50 values (the xylem tension causing 50% embolism) from Skelton *et al.* (2019), which
188 were measured on branches collected at the same time and using the same methods as branches
189 collected for hydraulic efficiency measurements reported here. However, P50 measurements had
190 few or no replicates per individual and were thus not suitable for branch-level analyses.
191

192 *Hydraulic traits*

193 Due to extremely long vessel lengths in oaks (often >1 m in branches of *Q. douglasii*, based on
194 pressurized branches recut at the basal end until air bubbles were seen at the distal end; RPS and
195 LDLA *pers obs*), classic hydraulic methods using stem segments were impossible without
196 considerable open vessel artifacts. Instead, we performed hydraulic measurements on terminal
197 branches of 1-2 mm basal diameter using the vacuum chamber method (Kolb *et al.* 1996). We
198 targeted current year growth when possible (similar to branch sampling for morphology), but
199 included up to three years of growth when the current year was <2 cm long and stem diameter
200 was not sufficiently large to fit in hydraulic tubing. For each terminal branch, all subtending
201 leaves were cut under water at the petiole with a razor blade, and the entire stem was inserted
202 into a vacuum chamber. Flow from a scale, through the branch and out the cut petioles was
203 induced by subjecting the stem to a ~60 kPa vacuum. Nevertheless, any stem that was suspected
204 of having an open vessel (i.e. any stem that had a high apparent conductance) was checked for
205 open vessels by attaching to pressurized nitrogen for ~10 minutes and checking under water for
206 air bubbles from the stem or petioles. The leaf area of all subtending leaves was measured via
207 flatbed scanner and ImageJ (Schneider *et al.* 2012), basal stem diameter at 4 radii averaged, and
208 the length of the stem and all branches measured with digital calipers.

209 Raw stem conductance was standardized two different ways. First, raw conductance was
210 standardized per unit leaf area, here termed k_{stem} , indicating leaf area-specific stem conductance
211 (i.e. not standardized by path length, so including the effects of differential stem growth in long
212 versus short stems, Table 1). Raw conductance was also divided by stem cross-sectional area and
213 multiplied by total stem length (including length of branches if stem was branched) to produce
214 sapwood area specific conductivity, or K_s .

215 Leaf hydraulic conductance was also measured on terminal branches (cut from the same
216 >1 m long branch as stem conductance) using the ‘rehydration kinetics’ (RK) method (Brodribb
217 & Holbrook 2003). Because leaves often had very small and irregular petioles, we measured
218 multiple leaves attached to a terminal twig. Leaf conductance was an order of magnitude lower
219 than stem conductance, meaning the effect of the stem in the conductance observed via the RK
220 measurements was negligible. Total leaf area for each sample was calculated via flatbed scanner
221 and ImageJ for each sample, and leaf-area specific leaf conductance, k_{leaf} was calculated. Only
222 measurements from leaves with an initial water potential < -0.2 MPa and > -2 MPa were
223 analyzed to avoid large measurement errors in samples with small pressure gradients or potential
224 embolism.

225

226 *Growth rate:*

227 We calculated growth rates for the common garden individuals based on a winter of 2017 survey
228 of tree diameter at 50 cm and stem height. We calculated total stem volume growth since
229 planting, assuming the stem was a cylinder with the diameter of the basal diameter and a height
230 of tree height, using only the largest stem of multi-stemmed individuals. Growth rates were
231 calculated for the wild trees from tree cores, which were collected via increment borer at 1.3 m

232 height, mounted, sanded, and 5 years worth of rings identified using a dissecting microscope.
233 The length of the 2013-2018 5-year growth period was measured via digital calipers and radial
234 growth was converted to Basal Area Increment (BAI) based on tree DBH. Tree BAI is a function
235 of tree size (Figure S2), so BAI was standardized for tree size by calculating the percent of size-
236 specific maximum Basal Area Increment (BAI) over the 2013-2018 period. Size-specific
237 maximum BAI (the fastest rate a tree of a given DBH was observed to grow) was calculated for
238 each tree's DBH based on the 90th quantile regression of BAI versus tree DBH for all study trees
239 (n=32) plus tree core data from 29 trees spanning five additional sites across California to
240 expand the range of sampled tree sizes (total DBH range 7.8cm-104cm, Figure S2). The
241 observed BAI was then divided by the maximum BAI for each tree to produce '% max BAI'.
242 Tree cores were collected in Oct of 2018, but could not be collected from one site due to loss of
243 site access (n=6 sites rather than 7).

244

245 *Variance decomposition analysis:*

246 We performed variances decompositions, separately in the garden and the wild, on all branch-
247 level trait measurements to quantify trait variation within canopy (among branches), among
248 individuals within populations, and among populations. We fit linear mixed-effects models
249 separately for the garden or the wild traits, with a fixed intercept term, a random intercept for
250 population and a random intercept for individual nested within population. We employed the
251 *lmer()* function from the *lme4* (v 1.1-28) and *lmerTest* (v 3.1-3) packages. We then extracted the
252 random effect variance parameters, and calculated the proportion of total trait variance that was
253 attributed to among-population differences (population random effect), individual differences
254 within populations (individual random effect) or variation within individual tree canopies
255 (residual variance). We also calculated the coefficient of variation (CV = trait mean / trait
256 standard deviation) for each trait in the garden and in the wild. Finally, to compare the total trait
257 variation in the garden versus in the wild while accounting for unequal sample sizes, we
258 bootstrapped variance estimates, randomly sampling with replacement each dataset 1000 times
259 with sample number set to the minimum sample size of the two datasets (wild versus garden) for
260 each trait. We then compared the median bootstrapped trait variance for the wild versus garden.

261

262 *Among-population trait differentiation and climatic variation*

263 We tested for significant among-population trait differences by averaging trait values per
264 individual and then performing one-way ANOVAs separately in the garden and in the wild, and
265 calculated the omega-squared (ω^2) as an estimate of the proportion of variance explained by
266 among-population differences. Replicate was never a statistically significant factor in the garden,
267 and was excluded from the final ANOVAs (fitted using the *aov()* function in the *stats* package, v
268 4.1.2). We then used AICc (Akaike's Information Criterion corrected for small sample sizes,
269 *AICc()* function from the *MuMin* package, v 1.43.17) to select the best single climatic predictors
270 of among-population differences for each trait. First, we determined whether a random intercept
271 for population was required to account for non-independence among individuals in a population
272 by fitting an 'over the top' fixed effects structure (Zuur *et al.* 2009), including mean annual
273 precipitation, mean annual potential evapotranspiration and mean minimum temperature) and
274 using likelihood ratio test to determine whether the population random effect was needed (using
275 the *gls()* and *lme()* functions from the *nlme* package, version 3.1-155). We then used AICc to
276 select the best climate predictor for each trait using linear models (*lm* in the *stats* package) or
277 linear mixed models with a population random intercept (*lmer* in the *lme4* package) and assessed

278 significance of the best predictor using t-tests, using Satterthwaite's degrees of freedom from the
279 *lmerTest* package (Kuznetsova *et al.* 2016). For the common garden, potential predictors
280 included only 30 year climate normals of mean annual precipitation ($PPT_{30\text{yr}}$), mean annual
281 potential evapotranspiration ($PET_{30\text{yr}}$), mean annual actual evapotranspiration ($AET_{30\text{yr}}$), mean
282 annual climatic water deficit ($CWD_{30\text{yr}} = PET_{30\text{yr}} - AET_{30\text{yr}}$), and mean annual minimum
283 temperature ($T_{\min 30\text{yr}}$). For wild traits, we also included growth year (2017-2018) weather
284 information as well: wet season (Nov-May) minimum temperature ($T_{\min\text{gy}}$), maximum
285 temperature ($T_{\max\text{gy}}$), precipitation (PPT_{gy}), potential evapotranspiration (PET_{gy}), actual
286 evapotranspiration (AET_{gy}) and climatic water deficit (CWD_{gy}), as well as the anomaly of the
287 2018 water year from the site 30 year normal (PPT_{anom} , PET_{anom} , AET_{anom} , CWD_{anom}). We
288 visually examined quantile-quantile plots and other patterns in the residuals to identify outliers
289 and ensure model assumptions were met.
290

291 *Trait-trait coordination*

292 To examine the magnitude of phenotypic (genetic plus plastic variation in the wild) and genetic
293 (variation in the garden) trait correlations, we calculated Pearson's correlation coefficients for all
294 pairs of individual-averaged traits in the wild and in the common garden. We visualized the
295 correlation structure using the *corrplot()* function in the *corrplot* package (v 0.92). We then used
296 a similar procedure to the bootstrapped variance comparisons to test for significant differences
297 between genetic and phenotypic trait correlations, randomly sampling individuals with
298 replacement from the entire wild and entire common garden datasets to produce two populations
299 of equal size to the smallest of the garden or wild complete pairwise observations, resampling
300 1000 times per trait combination. We then calculated the difference between the trait-trait
301 correlations in each bootstrapped pair of garden and wild datasets and determined the two-tailed
302 probability that the distribution of differences did not include 0 (e.g., $\alpha < 0.05$ if either the
303 2.5th percentile of differences was greater than zero or the 97.5th percentile of differences is less
304 than zero, $\alpha < 0.1$ if the 5th and 95th percentile range did not include zero, and $\alpha < 0.2$ if
305 the 10th to 90th percentile range did not include zero).
306

307 All code and data for analyses and figure generation can be found at
308 <https://github.com/leanderegg/BlueOakGarden.git>, and all data are also available on Dryad at
309 [insert Dryad link upon acceptance].
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312 **Results**

313 Genetic variation among populations was low in all morphological, allocation and
314 hydraulic traits in the common garden (Fig 1a). However, all traits except for stem sapwood
315 area-specific hydraulic conductivity (K_s) and leaf and stem vulnerability to embolism ($P50_{\text{leaf}}$,
316 $P50_{\text{stem}}$) showed substantial among-population variation in the wild. Among-population variation
317 in the wild was consistently 25%-30% of total trait variation in most traits, with SLA and LDMC
318 showing even larger among-population variation (46% and 40%, respectively, Fig 1b).
319 Meanwhile, branch-to-branch variation within tree canopies consistently made up the majority of
320 trait variation in the common garden, constituting >50% of total variation in all traits except WD
321 (42% of total) and over 75% of total variation in k_{leaf} , k_{stem} , and K_s (Fig. 1a). In the wild, within-
322 tree variation was typically less than 50% of total variation, except in $M_L:M_S$ and the three
323 hydraulic traits (Fig 1b).

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327 When traits were averaged to the individual, 40-60% of the total tree-to-tree variation in
328 almost all traits was between populations in the wild (Fig 2a) and population differences were
329 significant in 8 of 11 traits (all but K_s , $P_{50\text{leaf}}$, and $P_{50\text{stem}}$) plus growth (ANOVAs $p < 0.05$, Table
330 S2). Meanwhile, typically <30% of tree-to-tree variation was between populations in the garden,
331 and population differences were only significant in 2 of 10 traits (SLA and leaf size) plus growth
332 in the garden (Table S2). Leaf size was the one notable trait that showed significant and similar
333 among-population differentiation in both the wild and garden.
334

335 However, despite the consistent among-population variation in wild traits, climate
336 predictors (historical climate normals, meteorology of the water year of sampling, or the
337 sampling year anomaly from historical climate) very rarely explained differences among
338 populations (Fig. 2b). Based on AICc of linear or linear mixed models (when there was support
339 for a site random intercept, see Table S2), univariate climate predictors were only statistically
340 significant for four wild traits (Fig 2b) with WD decreasing with AET_{anom} , $P_{50\text{stem}}$ decreasing
341 (growing more negative) with $AET_{30\text{yr}}$, and $M_L:M_S$ decreasing and k_{stem} increasing with $T_{\text{min}_{\text{gy}}}$
342 (Figs S3,S4). (Fig 2b, Table S2). Meanwhile, in the garden three traits and growth were
343 significantly associated with source population climate (Table S2). In the garden, increasing
344 $PPT_{30\text{yr}}$ was significantly associated with decreasing wood density and increasing leaf size, while
345 increasing $PET_{30\text{yr}}$ was significantly associated with increasing SLA and decreasing growth (Fig
346 S3,S4).

347 While the among-population variance in the garden was always a small fraction of the
348 among-site variation in the wild, this did not generally result in decreased total trait variance the
349 garden (Figure 3). Bootstrapped estimates of the variance in individual averaged traits (i.e.,
350 among individual variance) generally showed larger median variance estimates in wild traits than
351 the common garden, but ratio of the garden variance to wild variance was only significantly less
352 than one (alpha <0.05) for SLA, LDMC, and WD. Meanwhile, $M_L:M_S$ and k_{leaf} had similar
353 variances in the wild and the garden despite significant among-population differentiation on the
354 landscape and not in the garden, and $A_L:A_S$ and k_{stem} had only marginally higher wild variances.
355 K_s , $P_{50[\text{stem}]}$ and $P_{50[\text{leaf}]}$ had similar variances in the wild compared to the garden and no
356 significant among-population differentiation in either location (Table S2), while growth could
357 not be compared because of differing metrics (% of max basal area increment vs 30 yr stem
358 volume). Ultimately, population-average trait values were entirely uncorrelated in the garden and
359 in the wild except for $M_L:M_S$ (Figure S2), even for the traits with similar amounts of total
360 variation in the two settings.
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363 *Trait coordination*

364 Trait-trait coordination was much stronger in the wild than in the common garden,
365 suggesting phenotypic correlations are not generally driven by genetic correlations or constraints
366 but rather by coordinated plasticity. Only six of 55 possible trait-trait correlations were
367 significant in both the garden and the wild (Fig. 4), almost all of which are unsurprising (e.g.,
368 $A_L:A_S \sim M_L:M_S$, $SLA \sim LDMC$) or mathematically related ($K_s \sim k_{\text{stem}}$ or $K_s \sim A_L:A_S$ because K_s
369 was calculated as $k_{\text{stem}} * A_L:A_S * \text{branch length}$). The main notable correlations consistent across

370 the garden and the wild trees were positive relationships between average leaf size and leaf vs
371 stem allocation on both an area basis ($A_L:A_S$) and a mass basis ($M_L:M_S$). Moreover, average leaf
372 size was much more strongly associated with variation in $A_L:A_S$ than number of leaves per
373 branch in both the garden and the wild (Fig. S3), suggesting that leaf expansion may be a key
374 regulator of leaf-to-stem allocation.

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380 Beyond these correlations, only three additional trait correlations were significant in the
381 garden, while 10 additional trait correlations were significant in the wild (Fig 4). The change in
382 trait-trait correlations from garden to wild was statistically significant ($\alpha < 0.05$) in four trait pairs
383 and marginally significant ($\alpha < 0.1$) in two more pairs (based on 1000 bootstrapped correlation
384 comparisons, Fig 5). The most striking change in trait coordination occurred amongst k_{leaf} , k_{stem}
385 and $A_L:A_S$. Whereas there was only weak coordination between k_{stem} , k_{leaf} and $A_L:A_S$ in the
386 garden, there was a strong positive correlation between leaf area-specific branch and leaf
387 conductance in the wild (significantly different in the wild vs garden, $p < 0.05$, Fig 5) as well as
388 strong negative relationships between both leaf and stem conductance and $A_L:A_S$. This plastic
389 increase in hydraulic integration in wild trees appears to be driven by leaf size, which is strongly
390 negatively correlated with k_{leaf} and k_{stem} in the wild (change in correlation is statistically
391 significant for k_{stem}). Across the landscape, trees with smaller leaves had lower $A_L:A_S$, but
392 consequently greater k_{leaf} and k_{stem} .

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395 *Trait-Growth relationships*

396 In the garden, traits were generally not strongly predictive of population average growth
397 (30 year height). Contrary to expectations, LDMC was positively and k_{stem} negatively correlated
398 with growth rates. Leaf size was the only trait correlated with growth in the expected direction,
399 with populations with larger leaves having higher average growth rates (Fig. S4). In the wild, no
400 traits were correlated with radial growth rates (calculated as the percent of maximum size-
401 specific Basal Area Increment), with the exception of K_s (Fig. S5), though growth was only
402 measured in six of the seven populations due to lost access at one site after initial trait sampling.
403 K_s was negatively correlated with growth, contrary to expectations.

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Discussion

406 We found very little among-population genetic differentiation but consistent among-
407 population variation across the landscape in morphological and hydraulic traits of a widespread
408 oak species. This landscape-scale plasticity could not be easily explained using gridded climate
409 or annual meteorological data, but drove trait-trait coordination – particularly of leaf and stem
410 hydraulic traits – that was otherwise lacking in the common garden.

411

412 *Traits in the common garden: little local adaptation*

413 In a relatively mesic common garden (978 mm of mean annual precipitation, greater than
414 all but two of the sampled populations, Table S1), we found very little evidence for genetically
415 based trait variation among populations. Populations showed significantly different growth rates

416 (height attained at 30 years) in the garden, but only SLA and leaf size showed significant among-
417 population variation (Figure 2). Among individual trees in the common garden, there was
418 remarkably little trait coordination to suggest strong genetic correlations among traits, even
419 though many of these traits are correlated across species (Mencuccini *et al.* 2019; Sanchez
420 Martinez *et al.* 2020). Moreover, this lack of coordination was not necessarily an artifact of
421 limited total trait variation in the common garden, as only three of 11 possible traits showed
422 significantly smaller variance in the garden than in the wild (Fig. 3). Thus, the trait variation
423 manifested in the garden was not merely the wild trait variance less among-site plasticity, and
424 neither the lack of trait coordination (Fig 4) nor the lack of correlation between wild and garden
425 trait values (Fig. S5) was likely driven by restricted garden trait variance.

426 At the same time, the only traits that showed expected relationships with growth rates in
427 the common garden were leaf to stem allocation traits ($M_L:M_S$ and potentially $A_L:A_S$), with
428 leafier populations showing faster growth, and leaf size, with larger leaved populations showing
429 faster growth. We conclude that changes to allometry were the primary drivers of functional
430 differences among populations in the common garden in line with classic predictions about the
431 drivers of growth rate variation (Lambers & Poorter 1992), and that this variation in allocation
432 was linked in part to genetically determined variation in leaf size (Fig. S3). Meanwhile, leaf dry
433 matter content (LDMC) and leaf-specific stem conductance (k_s) were significantly correlated
434 with growth rates, but in a direction contrary to expectations. For LDMC, we interpret this as a
435 consequence rather than a cause of growth rate variation (faster growing trees had accumulated
436 more photosynthate in their leaves by the sampling period and thus had higher LDMC), and for
437 k_s , rather than high conductivity promoting growth (Hajek *et al.* 2014) slower growth in high k_s
438 populations appears to be a consequence of high hydraulic efficiency in the two most arid
439 populations that grew slowly in the garden.

440

441 *Traits in the wild*

442 In contrast to the common garden results, all traits except K_s and $P50_{\text{stem, leaf}}$ showed
443 substantial among-population trait differentiation across *Quercus douglasii*'s geographic range.
444 While all traits exhibited large branch-to-branch variation within a canopy (in both the garden
445 and the wild), among-population trait differences were as large or larger than differences among
446 trees in the wild (Fig 1b, 2a). Thus, it appears that spatial variation in drought-related physiology
447 is substantial in blue oak, and is primarily driven by trait plasticity.

448 Surprisingly, this site-to-site trait variability was not strongly related to available site
449 climate data. Neither 30 year site climate normals nor meteorological data from the water year of
450 sample collection, nor the climate anomaly of the sampled year compared to climate normals
451 predicted among-site trait variation. For the four traits that were significantly predicted by site
452 climate, winter minimum temperatures ($T_{\min_{\text{gy}}}$) was the best predictor for two traits ($M_L:M_S$ and
453 k_{stem}) and a water balance metrics (some actual evapotranspiration metric, AET_{anom} and $AET_{30\text{yr}}$)
454 was only a significant predictor for two traits (WD and k_{leaf} , respectively). We hypothesize that
455 this discrepancy is the result of *Quercus douglasii*'s deep rooting strategy, which combined with
456 the substantial geologic and edaphic variation among the sampled sites to largely decouple the
457 actual water availability (the 'weather underground', sensu (McLaughlin *et al.* 2020)) from
458 above-ground climate.

459 Strikingly, the plasticity-driven trait variation across California resulted in strong trait-
460 trait coordination on the landscape, particularly among hydraulic efficiency and allocation traits.
461 Leaf and branch morphology and $P50$ were largely uncoupled from other traits in both the wild

462 and the common garden (Fig 4). However, k_{leaf} and k_{stem} significantly changed their correlation
463 strength from uncorrelated in the garden to positively correlated in the wild, and both traits
464 showed a strong correlation with both leaf size and $A_L:A_S$ in the wild. Collectively, this resulted
465 in strong integration across a leaf and stem ‘hydraulic module’, wherein trees with small leaves
466 had small $A_L:A_S$ ratios and high leaf area-specific leaf and stem hydraulic conductance. We
467 found no evidence for a tradeoff between safety and efficiency in either leaves or stems (Fig S6).

468 We also found very little evidence for trait-growth relationships in the wild, despite much
469 larger among-population trait differentiation. The only significant relationship was a decrease in
470 growth with increasing K_s , which may be consistent with increasing drought avoidance in the
471 driest populations (Fig S5). This lack of wild trait-growth relationship is perhaps not surprising,
472 given that both traits and environmental conditions and resources differ among populations,
473 making it difficult to disentangle cause versus effect.

474

475 *Leaf area-driven hydraulic coordination*

476 In theory, the coordination or integration of plant traits across tissues should optimize
477 whole-plant function (Reich 2014). However, perhaps partly as a result of traits rarely being
478 measured simultaneously for multiple tissues, this coordination is not universally observed
479 among tissues (Vleminckx *et al.* 2021) or types of traits (Sanchez Martinez *et al.* 2020), and the
480 actual mechanisms of this coordination (e.g., coordinated evolution, developmental constraints,
481 etc.) remain elusive. The leaf and stem hydraulic integration that we found across wild
482 populations suggests that, within individual species, plastically determined leaf size, presumably
483 coordinated by leaf expansion, may be a key mechanism coordinating hydraulic efficiency across
484 tissues.

485 We found little evidence for genetic correlations among hydraulic traits in a common
486 environment (Fig 4a), suggesting that hydraulic variation within species was not due to genetic
487 linkage or coordinated microevolution. However, strong hydraulic integration between the leaf
488 area-specific hydraulic conductance of leaves and stems across wild populations indicates
489 coordinated trait plasticity. This coordination seems to be mediated by allocation to leaf area
490 ($A_L:A_S$), which was largely driven by the average size of leaves (rather than leaf number, Figure
491 S3). Average leaf size had a larger coefficient of variation than stem diameter (0.41 versus 0.31,
492 respectively), and had a stronger negative correlation with both k_{leaf} ($\rho = -0.43$) and k_{stem} ($\rho =$
493 -0.54) than $A_L:A_S$ itself did with either trait ($\rho = -0.39$ and $\rho = -0.30$ for k_{leaf} and k_{stem}
494 respectively). Further supporting the importance of plasticity, average leaf size was uncorrelated
495 with either k_{leaf} or k_{stem} in the garden, and the increase in the correlation from garden to wild was
496 strong for both traits and statistically significant for k_{stem} ($p < 0.05$). Meanwhile, the more
497 commonly measured sapwood-specific branch conductivity (K_s), which is standardized for
498 branch xylem conductive area and path length, was highly variable but not differentiated among
499 populations (Fig 1) and unrelated to either leaf size or k_{leaf} in the wild. This may partly be due to
500 the difficulty of measuring path length for our K_s estimates, because in order to avoid open
501 vessels in this long-veined oak species we had to measure the conductance of whole terminal
502 branches cut at the petioles (rather than branch segments) and estimate the path length from the
503 total branch length, even though leaf attachment to the branch occurred along much of its length.
504 Thus, k_{stem} (conductance of the whole branch per unit leaf area) was likely a more accurate
505 measurement of hydraulic efficiency than K_s (conductivity per sapwood area for a 1cm stem
506 length) in this study.

507 Ultimately, it appears that whole-branch conductance of terminal branches and leaf
508 conductance were coordinated in the wild by plastic changes in leaf size, presumably regulated
509 by environmental cues governing spring leaf expansion, rather than changes in the xylem
510 efficiency itself. K_s , while highly variable, did not differ among populations either in the garden
511 or the wild (Fig 1) and therefore could not drive this pattern. A developmentally fixed hydraulic
512 architecture (in both leaves and stems) that then gets allocated to supply a variable amount of
513 leaf area based on leaf expansion presents a parsimonious mechanism for regulating whole-tissue
514 hydraulic resistance, as regulation of transpirational area may be much easier to regulate in
515 response to environmental cues through turgor driven leaf expansion than anatomical changes to
516 xylem efficiency. Moreover, the negative relationship between leaf size and k_{leaf}/k_{stem}
517 documented here contrasts with the lack of relationship between k_{leaf} and leaf size among species
518 and suggests a developmental constraint rather than adaptive mechanism.
519

520 *Management implications*

521 Our results from mature trees would indicate that genetically informed management or
522 restoration of blue oaks may not require strong consideration of the aridity of the source
523 materials, as mature tree drought resilience appears to be determined by canalized thresholds of
524 xylem vulnerability to drought (Skelton *et al.* 2019) and largely plastic adjustments to drought
525 avoidance-related traits (e.g. k_{branch} and k_{leaf}). While we could not predict trait variation across the
526 landscape based on site climate (Fig 2b), the substantial among-population variation in leaf-to-
527 stem allocation and hydraulic efficiency are presumably adaptive and therefore constitute plastic
528 adjustments to drought exposure by increasing plant hydraulic efficiency. This decreases the
529 minimum leaf water potential required to attain a given rate of transpiration (Whitehead & Jarvis
530 1981; Mencuccini *et al.* 2019; Trugman *et al.* 2019) and is quite consistent with within-species
531 adjustments to promote drought avoidance in numerous other systems (Mencuccini & Grace
532 1995; Martinez-Vilalta *et al.* 2009; Anderegg & HilleRisLambers 2016; Rosas *et al.* 2019;
533 Anderegg *et al.* 2021).

534 Our findings of limited local adaptation are also consistent with the relatively small
535 amount of local adaptation found in blue oak growth rates (Fig 1) and phenology (Papper &
536 Ackerly 2021), and the relatively high rates of gene flow in blue oak (Papper 2021). While other
537 California oak species have been found to show strong genetic structure across their range (Sork
538 *et al.* 2013; Gugger *et al.* 2021), evidence suggests that blue oak population differentiation across
539 its broad geographic distribution is more limited. Given the strong potential for plastic
540 adjustments to plant hydraulics documented here, this might suggest that most populations can
541 (and may) manifest more drought avoidant phenotypes in a warmer and drier future climate,
542 regardless of their climate history.

543 Two important caveats to our finding of limited drought-related local adaptation are 1)
544 that we only studied reproductively mature trees and 2) that we only studied traits in a relatively
545 mesic garden. Local adaptation at the earliest life stages may be most relevant for restoration,
546 and limited local adaptation in adult phenotypes does not guarantee limited local adaptation in
547 juvenile phenotypes. Moreover, we were only able to perform trait measurements in a relatively
548 wet common garden. If the expression of genetic differences depends on the environment – e.g.,
549 if there are strong GxE interactions for drought-related phenotypes – then our results could differ
550 entirely in a drier common garden location. It remains possible that genotypes from drier
551 populations have larger potential for plasticity (as documented in a *Eucalyptus* species, Mclean
552 *et al.* 2014), which could imply that the same source populations planted in a dry location could

553 show substantial among-population variation due to the dry-adapted populations manifesting
554 more plasticity than wet-adapted populations.

555

556

557 Conclusion

558 In a study of range-wide trait variation in blue oak (*Quercus douglasii*), we found little
559 evidence for local adaptation in any of numerous morphological or hydraulic traits but
560 substantial realized trait variation across the landscape. Our results suggest that this landscape-
561 scale trait variation involved plastic trait adjustments, and that this plasticity drove among-tissue
562 trait coordination. Thus, plastic adjustments, likely during the process of leaf development and
563 expansion, drive the coordinated manifestation of drought avoidant phenotypes with high
564 hydraulic efficiency in leaves and stems and increased carbon investment in stems relative to
565 leaves. However, these phenotypes could not be predicted by site climate and were poorly linked
566 to growth rates, indicating that our understanding of blue oak drought exposure and integrated
567 performance remains limited.

568

569

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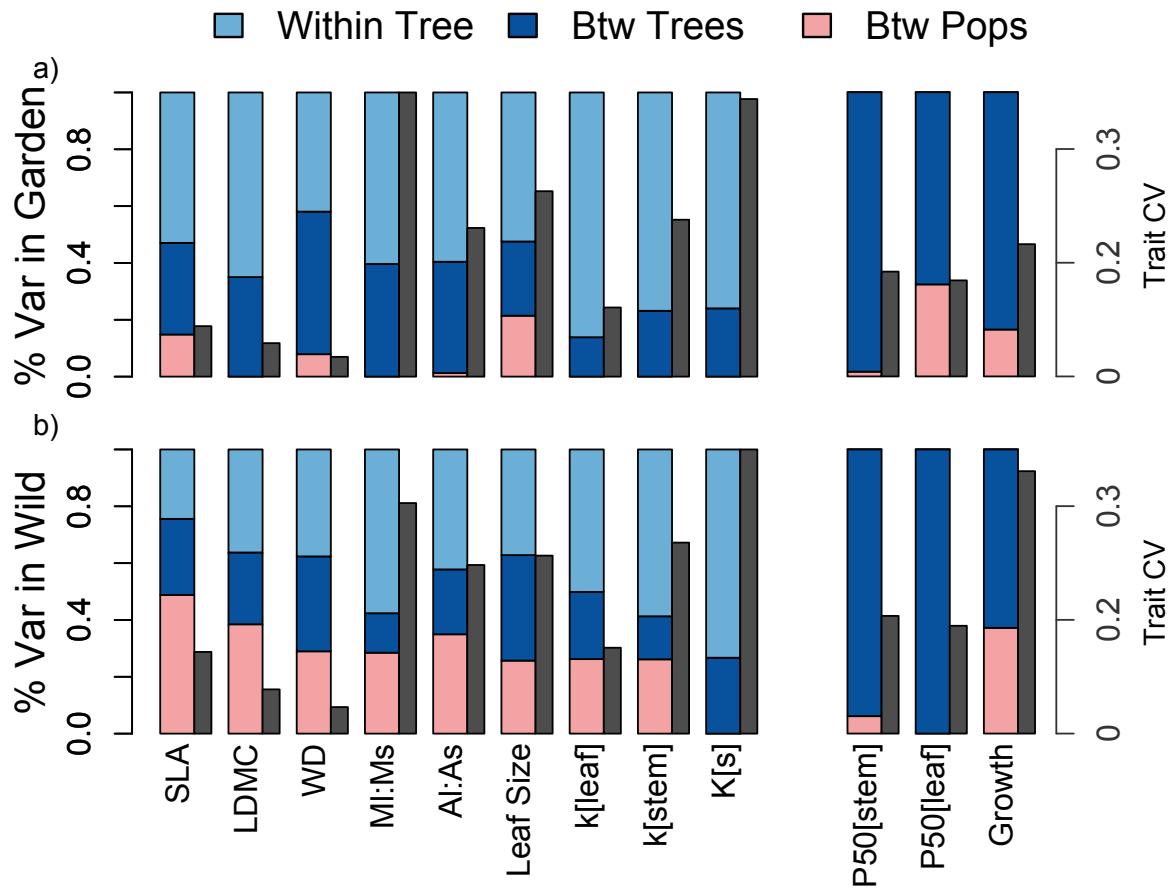
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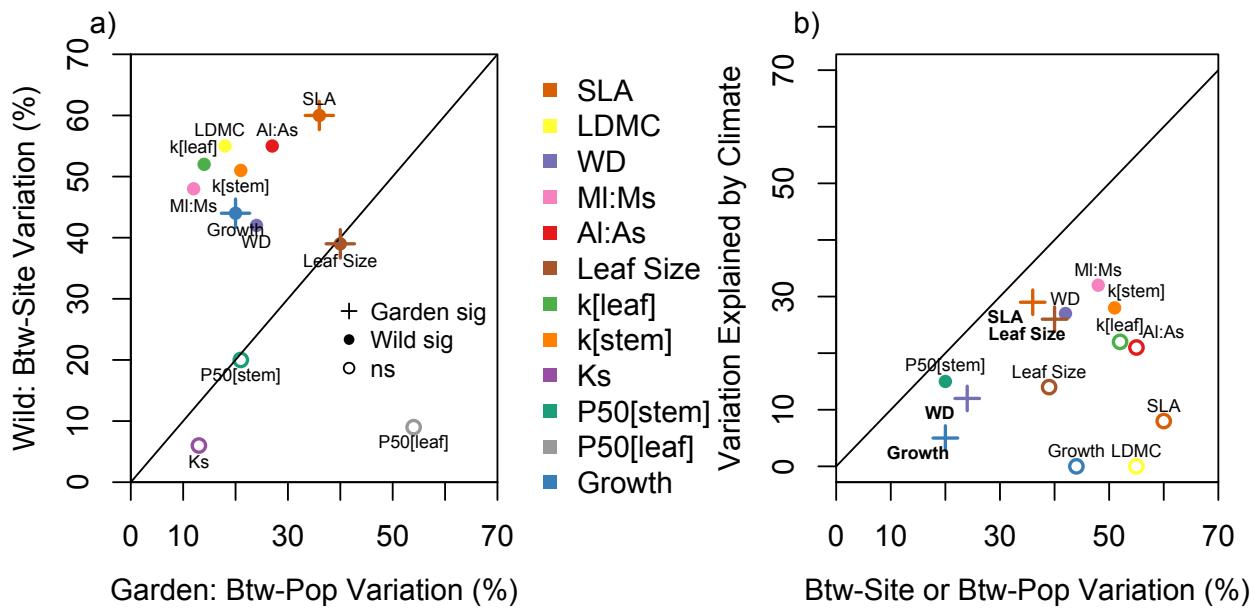
Table 1: Trait definitions and abbreviations as employed by this study.

| Trait | Definition |
|---------------------------|--|
| SLA | Specific leaf area ($\text{cm}^2 \text{ g}^{-1}$) |
| LDMC | Leaf dry matter content (g dry mass per g fresh mass) |
| WD | Wood density |
| $M_L:M_S$ | Terminal branch leaf dry mass to stem dry mass ratio (g/g) |
| $A_L:A_S$ | Terminal branch leaf area to sapwood area ratio ($\text{cm}^2 \text{ mm}^{-2}$) |
| Leaf size | Average area of a single leaf based on all leaves on a terminal branch (cm^2) |
| k_{leaf} | Leaf conductance per unit leaf area ($\text{mmol m}^{-2} \text{ s}^{-1} \text{ MPa}^{-1}$) |
| k_{stem} | Leaf area-specific stem conductance of full current year terminal branch ($\text{mmol cm}^{-2} \text{ s}^{-1} \text{ kPa}^{-1}$) |
| K_s | Sapwood area-specific stem conductivity per branch length ($k_{\text{stem}} * A_L:A_S * \text{length}$, $\text{mmol cm s}^{-1} \text{ kPa}^{-1}$) |
| $P50_{\text{leaf, stem}}$ | Leaf and stem P50 measured with optical technique from Skelton et al. 2019 |
| Growth | Garden: stem volume attained at 30 yrs, based on basal diameter and height of largest stem assuming cylindrical stem. Wild: percent of size-specific maximum basal area increment (based on rangewide 90 th percentile BAI at a given DBH) |



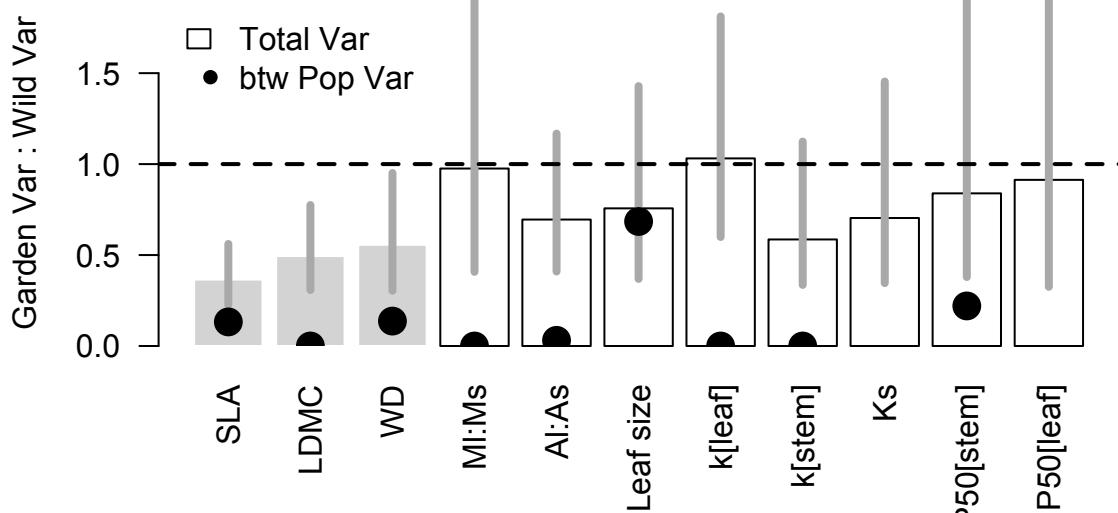
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Figure 1: Variance decomposition of all branch-level measurements in the common garden (a) and wild source populations (b). Grey bars beside the colored bars show the magnitude of the trait coefficient of variation. $P50_{stem}$, $P50_{leaf}$ and Growth do not have replicates within tree, so only contain between tree and between population variance components.



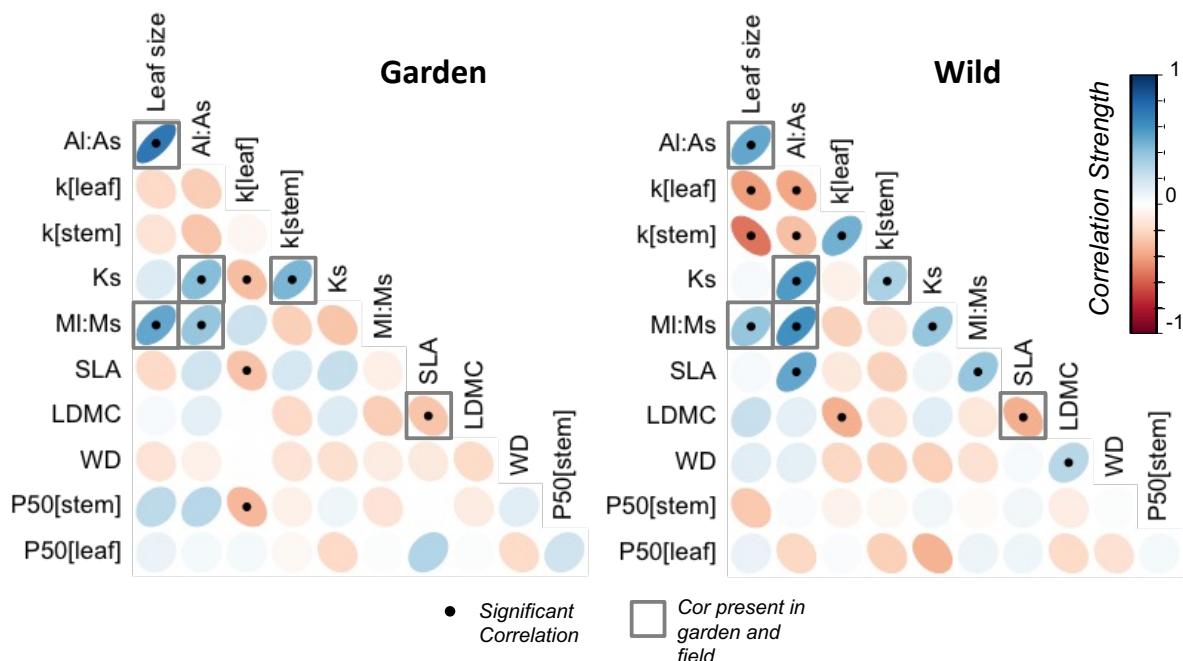
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Figure 2: (a) % of the total tree-to-tree variation attributable to population in the garden versus attributable to sites in the wild. Traits with significant between-site variation (ANOVA $p < 0.05$) in the wild are shown as filled points, while traits with significant between population variation in the garden are shown with crosses. (b) The among-population and among-site variation that could be explained with climate variables. Y-axis shows R^2 of best climate predictor based on AICc, filled points indicate predictors that are statistically significant for wild traits, open points show traits with significant among-population differentiation but non-significant climate predictors, and crosses with bold text show garden traits with significant climate predictors (Table S2). Black line shows 1:1 relationship.



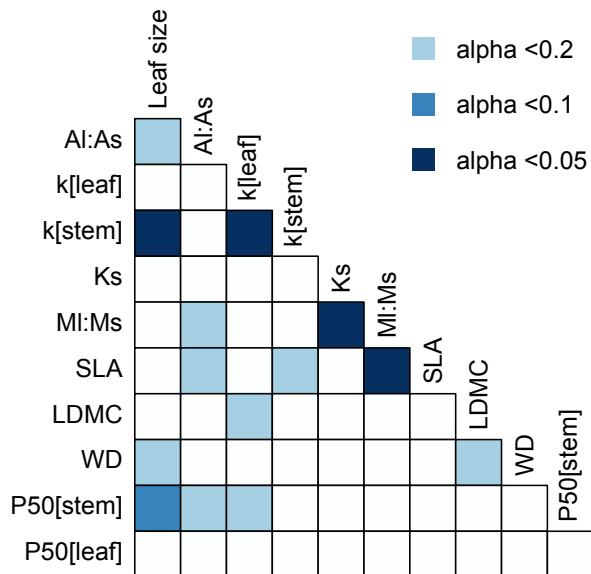
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Figure 3: Ratio of trait variance in the common garden compared to the wild (values <1 indicating more trait variance in the wild). Bars show the ratio of total trait variance (median of 1000 bootstrapped variance estimates, lines show 5th – 95th percentile of ratio), gray bars indicate significantly lower variance in the garden. Points show the ratio of the between-population variance component alone (Ks and P50_{leaf} had 0 estimated between-population variance in the wild and thus no points).



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Figure 4: Tree level trait-trait correlations in the garden (a) and in the wild (b). Ellipses and color show direction and strength of the correlation, points show statistically significant relationships, and grey boxes show relationships that are significant in both the garden and the wild.



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Figure 5: Multiple trait correlations were significantly different in the wild versus the garden (based on 1000 bootstrapped comparisons of correlations), particularly $k[\text{stem}]$ and $k[\text{leaf}]$ (significant correlation between leaf and stem hydraulic efficiency in whole terminal branch tissues in the field but not the garden) and in relationships relating to leaf size (again suggesting something interesting is going on with the drivers of plasticity in leaf expansion/development that leads to phenotypic integration in the wild).