

1 **Leaf shape and size variation in bur oaks: An empirical study and simulation of sampling**
2 **strategies**

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16

17 **ABSTRACT**

18 PREMISE: Oaks are notoriously variable in leaf morphology, but little is known regarding the
19 partial contributions of climate, population, latitude, and individual tree to total variation in leaf
20 morphology. This study examines the contributions of within-tree, among-tree, and among-site
21 variation to the total variation in leaf morphology in bur oak (*Quercus macrocarpa*), one of
22 North America's most geographically widespread oak species.

23 METHODS: Samples were collected from four sites each at northern, central, and southern
24 latitudes of the bur oak range. Ten leaf size traits were measured, and variance in these traits and
25 eight ratios was partitioned into tree, population, and latitude components. We then
26 parameterized a series of leaf collections simulations using empirical covariance among leaves
27 on trees and trees at sites.

28 KEY RESULTS: Leaf size measurements were highly responsive to latitude. Site contributed
29 more than tree to total variation in leaf morphology. Simulations suggest that power to detect
30 among-site variance in leaf morphology can be estimated most efficiently with increases in either
31 leaves per tree (10-11 leaves from each of 5 trees) or trees per site (5 leaves from each of 10+
32 trees).

33 CONCLUSIONS: Our study demonstrates the utility of both simulating sampling and controlling
34 for variance in sampling for leaf morphology, whether the questions being addressed are
35 ecological, evolutionary, or taxonomic. Simulation code is provided to help researchers plan
36 sampling strategies to maximize the ability to detect among-site variance in leaf morphology.

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38 Keywords: climate; Fagaceae; latitude; leaf morphology; leaf size; *Quercus macrocarpa*;
39 sampling simulation

40

41 Running head: Leaf morphological variation in bur oak

42 Manuscript received _____; revision accepted _____.

43

44 INTRODUCTION

45 Leaf morphology variation strongly influences species' ability to compete and survive in different
46 environments (Givnish, 1987). It has long been recognized that there is a correlation between
47 temperature and the proportion of species exhibiting leaf dissection and tothing, and for more
48 than a century this correlation has been used to model temperature changes in paleobotanical
49 studies (Bailey and Sinnott, 1915, 1916; Greenwood et al., 2004; Royer and Wilf, 2006). Leaf size
50 similarly has a well demonstrated correlation with temperature and resource availability (Bragg
51 and Westoby, 2002; Peppe et al., 2011; McKee and Royer, 2017; Wright et al., 2017; Li et al., 2020),
52 and traits such as compounding and phyllotaxy, base and apex morphology, leaf shape, and
53 epidermal pigmentation vary along gradients of light availability, nutrient availability, soil
54 moisture, temperature, or combinations of these (Givnish, 1987; Schmerler et al., 2012). In a global
55 field study from 92 sites (Peppe et al., 2011), multiple regressions of climate (both precipitation
56 and temperature) on leaf area, tooth number, and percent of species at the site with tothing
57 showed relatively high predictive ability, inferred from the low standard error of the models
58 ($\pm 4^{\circ}\text{C}$). However, while the sign of this correlation—more tothing and lobing in cooler areas—
59 is convergent across clades and geographic regions, the slope of the relationship between climate
60 and leaf morphology varies among species (McKee et al., 2019), geographic regions
61 (Greenwood et al., 2004; Aizen and Ezcurra, 2008), and phylogenetic lineages (Little et al.,
62 2010; Burnham and Tonkovich, 2011; Walls, 2011).

63 Many of these traits vary both among and within species, and correlations between
64 community-weighted mean trait values at the site level are mirrored within species on short time
65 scales, with tothing and leaf lobing correlated with cooler temperatures in most species studied
66 as well as across communities (McKee and Royer, 2017; McKee et al., 2019). Moreover, the
67 morphology of leaves can vary highly within communities (Givnish, 1987). Within forest trees in

68 particular, variation due to position on the tree (Blue and Jensen, 1988; McCarthy and Mason-
69 Gamer, 2019), light availability (Abrams and Kubiske, 1990; Ducrey, 1992), drought (Abrams,
70 1994; Abrams et al., 1994) as well as genetic differences among trees within species (Abrams,
71 1994; Ramírez-Valiente et al., 2017) all contribute to variation in leaf shape and size. Moreover,
72 while sampling of a small number of leaves per population has been argued to be sufficient for
73 detecting site level patterns in climate based in paleobotanical studies (Royer et al., 2005; Peppe
74 et al., 2011), the relative contribution of within-tree, among-tree within-population, and among-
75 population variation to total morphological variation is not clear in many tree species, leading to
76 observations for example that variation among leaves on a single tree is sometimes as great as
77 the variation observed among named species (e.g., McCarthy and Mason-Gamer, 2019).

78 Oaks have long been noted for their particularly variable morphology at all levels (among
79 leaves on a single tree, among trees of a single population, and among populations of a single
80 species). Detailed studies in oaks have utilized either linear measurements (Baranski, 1975; Blue
81 and Jensen, 1988; Bruschi et al., 2003) or landmark approaches (Jensen, 1990). Both approaches
82 have demonstrated that while variation among positions within a tree in both leaf shape and size
83 may exceed variation among sites, overall variance is generally greater among sites. These
84 papers have highlighted that studies investigating among-population divergence patterns can
85 minimize within-individual morphological variance by holding sampling season and leaf position
86 on the tree constant (i.e., high or low on the tree and disposed toward the edges or inside of the
87 canopy) (Sokal et al., 1986; Blue and Jensen, 1988; Bruschi et al., 2003). Understanding these
88 sources of variance in leaf shape and size is foundational to understanding how introgression,
89 adaptation, and neutral variation influence leaf morphology both among and within species
90 (Jensen et al., 1984; Howard et al., 1997; Kremer et al., 2002; González-Rodríguez et al., 2004;

91 González-Rodríguez and Oyama, 2005) and the balancing act that trees face in maximizing
92 photosynthetic efficiency while minimizing the risks of drought, freezing, herbivory and other
93 stresses (Wright et al., 2004). However, it is not clear what sampling strategy (leaves per
94 individual, individuals per population) is most efficient for estimating among-population
95 differences in leaf size and shape. Whereas simple simulation tools exist for planning sampling
96 strategies for population genetics (Hoban et al., 2013; Hoban, 2014) and conservation of genetic
97 diversity (Hoban, 2019; Hoban et al., 2020), morphological sampling strategies that take into
98 account covariance among leaves on a tree, among trees in a population, and among traits
99 measured are lacking. Given that resources for sampling are limited, tools to help plan sampling
100 strategies would make it possible to answer questions more definitively with the same amount of
101 field work.

102 We sampled leaves across a broad geographic range of bur oak (*Quercus macrocarpa*
103 L.), one of North America's most geographically widespread oak species, which ranges from
104 Manitoba to the Gulf of Mexico (Fig. 1) to (1) quantify the relative contributions of within-tree,
105 among-tree, and among-site variation to the total variation in leaf morphology in bur oak; (2) use
106 this information to simulate how much sampling is required to detect among-site differences in
107 leaf morphology; and (3) test the support for our observations in field and herbarium that leaf
108 size and leaf-lobing increase from north to south in bur oak. Bur oak serves as an excellent
109 model species for this study because it has exceptionally high morphological variation
110 (Hamerlynck and Knapp, 1994; Koenig et al., 2009) and an extensive distribution, ranging from
111 Manitoba to the Gulf of Mexico (Little, 1971; Stein et al., 2003). The species also exhibits high
112 within-population molecular genetic variation (Schnabel and Hamrick, 1990; Garner et al., 2019;
113 Hipp et al., 2019), suggesting that an investigation of the leaf morphological variation among vs

114 within sites is appropriate as a precursor to future studies of what environmental factors
115 contribute to morphological variation in bur oak leaves.

116

117 **MATERIALS AND METHODS**

118 *Collections and site attributes*—During the summer and fall of 2017, samples were collected
119 from four sites each at northern, central, and southern latitudes of the bur oak range (Fig. 1).
120 Sites were selected in conjunction with sampling for ongoing population genetic studies of
121 *Quercus macrocarpa* (Garner et al., 2019; Hipp et al., 2019) with the criteria that (1) preliminary
122 collections suggested they would have numerous bur oaks, and (2) additional white oaks were
123 present at the site or nearby. Most were forested, but some (e.g. The Morton Arboretum, Prairie
124 Moon Nursery) were savannas. The northern sites sampled were located in Manitoba
125 (Assiniboine Park, Whiteshell Provincial Park, and Spruce Woods Provincial Park) and
126 Minnesota (The University of Minnesota – Twin Cities). The central sites sampled were located
127 in Illinois (The Morton Arboretum), Indiana (Burr Oak Woods), Iowa (Cherokee Park Trail), and
128 Minnesota (Prairie Moon Nursery). The southern sites sampled were located in Oklahoma
129 (Tallgrass Prairie Preserve, Mohawk Park, Red Rock Canyon State Park) and Missouri (Buttin
130 Rock Access). Trees selected at each site were mature, full-size trees; where possible, trees at a
131 given site were located a minimum of 100 feet from each other. For each site, latitude and
132 longitude were recorded to a precision of 5 decimal places (Table 1). We extracted 19 bioclim
133 variables from the WorldClim database (resolution = 1 km²) and linked them to our dataset in R
134 v. 3.4.4 (R Core Team, 2018) using raster v 2.6-7 (Hijmans, 2017) and sp_1.4-2 (Pebesma and
135 Bivand, 2005; Bivand et al., 2013) packages. The map of collection sites was made using maps
136 3.3.0 (Becker et al., 2018).

137 Three bur oak trees were sampled from each site using a pole pruner at two or four
138 meters in height, based on tree height. For each sample, a terminal branch was cut down from
139 each of the cardinal directions (N, S, E, W), determined using a compass. Only outermost
140 branches were sampled. Two endmost leaves were removed from each branch and immediately
141 pressed, for a total of 8 leaves per individual, 272 leaves overall. If the endmost leaves were
142 highly damaged, the next leaves in from the end were selected. Leaves that were highly
143 misshapen or broken were excluded from analyses (see 'use' field in dataset archived in GitHub,
144 which indicates which leaves were excluded from analysis). Leaves were dried in a standard
145 herbarium drier prior to measuring, then redried at 49° C for a minimum of 48 hours and
146 weighed on a PB303 Delta Range scale to obtain dry mass.

147

148 ***Morphological Measurements***—Ten size measurements (mm) were made on each leaf
149 using ImageJ (Schneider et al., 2012): blade length (bladeL), blade width (bladeW), width of
150 blade between deepest pair of sinuses (sinusMinW), petiole length (petioleL), petiole width
151 (petioleW), length of lamina from base to widest point (bladeLtoWidestPoint), width of blade
152 between pair of sinuses just above the deepest pair (sinusNextW), total length (BL.PL), leaf base
153 angle (bladeBaseAngle), and leaf area (Area) (Table 2, Fig. 2). Seven ratios were also calculated
154 from these measurements to distinguish leaf shape from leaf size (González-Rodríguez and
155 Oyama, 2005): petioleL / BL.PL (PL.TL); sinusMinL / sinusNextL (SinusRatio); bladeL /
156 bladeW (BL.BW); petioleL / petioleW (PL.PW); BL.BW / PL.PW (BL.BW.over.PL.PW);
157 bladeL / bladeLtoWidestPoint (BL.BLWP); lobedness, calculated as blade width between the
158 deepest sinuses divided by total blade width, abbreviated (sinus.v.width); and specific leaf area

159 (SLA), calculated as leaf blade area / leaf blade mass (Table 2). A panel of significant
160 regressions was created using the R core functions and gridExtra 2.3 (Auguie, 2017).

161 To investigate lobedness using more complex morphometric approaches, black and white
162 silhouettes of each leaf image were created using ImageJ and converted into jpeg files, with
163 petioles whited out manually. The jpeg files were then imported into R and converted into
164 outlines using the R package Momocs v 1.3.2 (Bonhomme et al., 2014). An additional set of 40
165 leaves that did not import well into Momocs or had leaf outlines that did not impair manual
166 measurements but that were badly non-representative of typical leaf form were deleted at this
167 stage (see scripts 05a and 05b in the GitHub repository for enumeration of these). We initially
168 investigated shape variation using elliptical Fourier analysis (EFA), which generates shape-
169 representative variables that are independent of size (Crampton, 1995) and is well suited to
170 comparing complex outlines that vary in shape and lobedness (Tracey et al., 2006). For these
171 analyses, we normalized the outlines using four landmarks placed on the top, bottom, left, and
172 right of each outline and analyzed the leaf outlines using 17 harmonics (the default setting).

173 We also used Momocs to measure circularity (as the square of perimeter over the area)
174 (Rosin, 2005) and Haralick's circularity (as the mean distance from the leaf centroid to the
175 perimeter pixels divided by the standard deviation of those distances) (Haralick, 1974).
176 Haralick's circularity is less sensitive to shape raggedness than the standard measure of
177 circularity and increases with increasing circularity; standard circularity decreases with
178 increasing circularity. We aggregated both circularity measures to individual and then
179 individuals to site to examine site-level effects of latitude on leaf circularity using simple least-
180 squares regressions.

181

182 *Statistical Analysis—Linear Regressions and ANOVA*—All statistical analyses were
183 conducted in R. Seventeen least squares were performed on all leaf linear measurements using
184 the lm function to assess which leaf traits were most responsive to latitude at the site level,
185 aggregating leaf traits first to tree, then tree mean trait values to site. An additional regression
186 was performed of Haralick circularity on latitude, at the site level. Data were visualized using
187 ggplot2 3.3.2 (Wickham, 2009). In addition to simple regressions, we corrected for size by
188 conducting multiple regressions for all of our leaf traits using the lm function and including
189 blade length (bladeL) as a covariate. We used data scaled to a mean of zero and unit variance.

190 We performed a principal component analysis (PCA_{MORPH}) on all scalar measurements
191 and ratios using the prcomp function. The point MN-MG788 was removed prior to analysis
192 because it significantly skewed the ordination. Two-dimensional nonmetric multidimensional
193 scaling on a Euclidean distance matrix based on principal component axes was used to visualize
194 the data. The scaling type was ‘centering’ with PC rotation. We used the ordiellipse function in
195 vegan 2.4-5 (Oksanen et al., 2017) to plot bounding ellipses on our ordination.

196 Two-way ANOVA was used to assess the relative contributions of site and tree to the
197 total variation in bladeL, SLA, PC1_{MORPH} and PC2_{MORPH}. Principal components one and two
198 were extracted from the principal component analysis mentioned above and attached to our
199 original dataset. ANOVA was conducted on the linear model of bladeL, SLA, PC1_{MORPH}, and
200 PC2_{MORPH} regressed against site and tree. We chose PC1_{MORPH} and PC2_{MORPH} for this analysis
201 because together they accounted for 52.5% of the variance.

202

203 *Simulations of sampling strategies*—We assessed the effectiveness of alternative
204 sampling scenarios to distinguish differences among populations by using our estimates of

205 variation to generate simulated morphological datasets for 20 populations that ranged from three
206 to 12 trees per site and three to 12 leaves per tree, a total of 100 sampling strategies. For each
207 strategy, we simulated 100 replicate datasets of all ten direct morphological measurements using
208 a hierarchical simulation strategy, using the data we collected to parameterize the simulation. For
209 each replicate, site-level means for all 10 traits were drawn from the multivariate normal
210 distribution with trait means and covariance \mathbf{C}_{site} estimated from observed site means for all
211 traits; \mathbf{C}_{site} is thus based on variance within and covariance among traits that we observed,
212 averaged for each site. Tree-level means were then drawn from the multivariate normal
213 distribution with the simulated site-level means and the covariance matrix \mathbf{C}_{tree} estimated from
214 tree means at each site and averaged across sites: tree-level means were thus assumed to have a
215 constant variance and covariance among sites. Finally, individual leaf measurements for each
216 tree were drawn from the multivariate normal distribution with means from the second
217 simulation stage and covariance matrix \mathbf{C}_{leaf} estimated from the leaf measurements for each tree
218 separately, then averaged across trees.

219 The resulting 100,000 data matrices ranged from 180 to 2,880 simulated leaves, with trait
220 covariance and variance among leaves within trees, among trees within populations, and among
221 populations modeled according the measurements we made for this project. Because leaf size
222 showed particularly strong variation among populations, we utilized ANOVA of bladeL on site +
223 tree, combined with Tukey's Honest Significant Different (HSD) method to assess the number of
224 populations that could be differentiated from one another in each simulated data matrix. The
225 number of letters needed for a compact letter display using Tukey's HSD at $\alpha = 0.05$ was used as
226 a proxy for the number of groups that could be distinguished for each simulated dataset. Both the
227 average number of groups distinguished for each simulated dataset and the percent of

228 simulations that distinguish at least 50% of populations (10 / 20) are reported as estimates of
229 statistical power. All simulations were conducted in R using mvtnorm v 1.0-11 (Genz and Bretz,
230 2009; Genz et al., 2019) (Genz et al. 2017), and code for performing simulations is archived in
231 GitHub and Zenodo (<https://github.com/andrew-hipp/oak-morph-2020>;
232 <https://doi.org/10.5281/zenodo.4213821>). The simulation code can be installed as package
233 ‘traitsPopSim’ from GitHub (<https://github.com/andrew-hipp/traitsPopSim>) and run using
234 multivariate traits collected in a similarly structured design (measurements nested within
235 individuals nested within sites; sample data included in the package are from the current study).

236

237 **RESULTS**

238 *Analysis of empirical data*—Among the size characters, bladeL, bladeW, BL.PL, petioleW, and
239 Area all showed significant variation in response to latitude (Table 3, Fig. 3). Petiole width was
240 the size trait that was the most significant ($P < 0.001$). Petiole length, sinusMinL, sinusNextL,
241 and blade base angle were not significantly predicted by latitude (Table 3). Two ratios were
242 significantly correlated with latitude: SLA ($r^2 = 0.466$, $P = 0.015$) and the ratio of sinus depth to
243 leaf width (sinus.v.width, a proxy for lobedness; $r^2 = 0.415$, $P = 0.024$) (Table 3). In regressions
244 controlling for size by including bladeL as a covariate, sinusNextL ($P = 0.021$), petioleW ($P =$
245 0.017), bladeL ($P = 0.012$) and SLA ($P = 0.011$) were the only traits significantly affected by
246 latitude alone (Table 3; Fig. 3). Regressions of all traits measured, significant or not, are
247 presented in the supplement (Supplemental Fig. S1). Standard circularity (perimeter squared over
248 area) was strongly affected by latitude ($r^2 = 0.506$, $P = 0.0043$; Fig. 4), Haralick circularity
249 (mean distance from leaf centroid to boundary pixels over the standard deviation of these

250 distances) was weakly predicted by latitude ($r^2 = 0.259$, $P = 0.0631$; Fig. 4). Under both
251 measures, southern leaves exhibited stronger lobing, northern leaves exhibited greater circularity.

252 PCA on the EFA yielded very high loading on PC1 (58%), very low on PC2 (8%), and a
253 strong curvilinear relationship between PC1 and PC2 (Supplemental Fig. S2). This non-
254 independence between PC1 and PC2 can arise because variation is broad, such that the ends of
255 the PC cloud have little in common, or because the variation is dominated by a single variable
256 (Minchin, 1987). In our study, PC1 was dominated by size (Pearson's product moment [r] =
257 0.251 for blade width, 0.227 for blade area) and latitude ($r = -0.213$), and PC2 was more
258 strongly associated with shape ($r = 0.395$ for the ratio of blade length to blade width, -0.375 for
259 width of the sinus distal to the deepest sinus, 0.348 for the ratio of the width of the blade in the
260 deepest sinus width of the blade in the second-deepest sinus), and to a lesser extent leaf blade
261 width ($r = -0.240$).

262 The effects of site and tree on bladeL, SLA, and the first two axes of the morphological
263 (non-EFA) ordination (Supplemental Fig. S3) were significant based on ANOVA ($P \ll 0.001$;
264 Table 4). Although site and tree both had significant effects, site contributed more than tree to
265 the total variation in leaf morphology (F-values for site range from 30.38–41.76, while F-values
266 for tree range from 5.83–12.4). Mean annual temperature among our sites ranged from 2.1–
267 15.3°C, and mean annual precipitation from 460 – 1121 mm. On average, leaf bladeL averaged
268 34.0 mm shorter and SLA 50.39 mm²/g greater for each increase 10 degrees in latitude
269 (northward).

270 Regressions of individual traits on site-level temperature and moisture conditions inferred
271 from BioClim closely matched regressions of those same traits on latitude. The latitudinal
272 gradient in our study correlated tightly with climate: increases in latitude entail decreases in

273 mean annual precipitation (Bio12; $R^2 = 0.6803$, $p < 0.01$) and temperature (Bio1; $r^2 = 0.99$, $p \ll$
274 0.01), and an increase in temperature seasonality (Bio4; $R^2 = 0.97$, $p \ll 0.01$) (Fig. 5). As a
275 consequence, climate is not considered further in this study, but only latitude.

276

277 *Analysis of simulated data*—The mean number of groups distinguished in our
278 simulations ranged from 5.49 to 10.41, and the probability of distinguishing 50% (10 / 20) of the
279 populations based on blade length ranged from 0.01 to 0.71 (Fig. 6). The sampling strategy we
280 implemented for this study, 3 trees per site, 8 leaves per tree, had a power of only 38% to
281 identify a number of groups equal to 50% of the sites sampled. Increasing power to at least 50%
282 would entail increasing sampling to 11–12 leaves from each of 5 trees, 5 leaves from each of 10–
283 11 trees, or any of a number of scenarios intermediate between these extremes.

284

285 **DISCUSSION**

286 Our study has three important findings. First, among-tree and among-site variation
287 contribute significantly to leaf shape and size variation in bur oaks. Consequently, within-
288 individual and within-population sampling are both important components of a sampling strategy
289 aimed at characterizing among-population variation in oak morphology. This complements
290 observations of high variance in temperate tree leaf morphology (Bruschi et al., 2003; Apostol et
291 al., 2017; McCarthy and Mason-Gamer, 2019), demonstrating that among-site variation
292 contributes most strongly to total leaf variation, but that within-site and within-tree sampling are
293 important to detecting among-site variation in leaf shape and size. Second, we implement a
294 general parametric simulation method and use it to demonstrate that our sampling strategy,
295 which included 8 leaves from different positions on each of 3 trees per site, was not optimal for

296 resolving among-site variation, even if it was sufficient to demonstrate the relationship between
297 morphology and latitudinal gradients. This simulation approach and the package provided
298 (traitsPopSim) can serve as tools to guide morphological sampling in similar hierarchical studies,
299 where sites are composed of multiple individuals and individuals are each represented by
300 multiple measurements. Finally, our study demonstrates that leaf size and lobing decrease from
301 south to north in bur oak, while specific leaf area increases. In cross-species comparisons, leaf
302 size and SLA generally covary, suggesting that adaptive leaf variation in bur oak may rest in part
303 on a tradeoff between leaf size and lobing. Our study of one of North America's most
304 widespread oak species is thus a jumping-off point for understanding adaptive leaf variation
305 across the oaks of the Americas.

306

307 *Leaf size and shape variance are influenced by population and individual*—Our results
308 show that among-site variance for all traits investigated ($F_{11,236} = 30.38\text{--}41.76$) contributes more
309 to total variance in leaf morphology than among-tree variance ($F_{11,236} = 5.83\text{--}12.42$), though both
310 variance components are significant ($P \ll 0.001$; Table 4). This ability to distinguish among
311 sites is important in relating leaf variation to latitude or climatic predictors and measuring the
312 slope of the relationship resulting from selective pressures along climatic gradients (Wright et
313 al., 2004). Moreover, our results demonstrate that sampling three trees per site, and eight leaves
314 per tree is sufficient to correlate shape and size to latitude and climate. However, while among-
315 site variance is higher than among-tree variance within sites (Table 4), the variance we observe
316 among leaves within a single tree is still quite high. A previous study (Bruschi et al., 2003) found
317 that among-leaf morphological variance on a tree is higher than among-tree variance for most
318 traits investigated, and that this was in accord with findings from earlier work (Baranski, 1975;

319 Blue and Jensen, 1988). However, in Bruschi (2003), leaves were sampled from both inner and
320 outer positions on the branch to maximize variance. In our study, we deliberately minimized this
321 source of variance by sampling leaves at a relatively constant height and all from the outer
322 branch position, and we further selected the endmost leaves from each branch sampled.

323 *Simulating sampling strategies*—The simulations we conducted of alternative sampling
324 strategies suggests the strategy we selected of three trees per site and eight leaves per tree has
325 only a 38% probability of distinguishing 50% of 20 populations drawn at random from
326 distributions we observed. It may well be that our difficulty relating shape to climate is due to a
327 lack of sampling within sites and trees. Based on the variance observed in leaf length alone,
328 achieving a 50% probability of distinguishing 50% of populations would require 11–12 leaves
329 from each of 5 trees per site, 5–6 leaves from each of 11–12 trees per site, or something in
330 between (Fig. 6).

331 Our simulations suggest two recommendations for others conducting similar studies.
332 First, researchers are recommended to minimize the high within-individual variance observed in
333 previous studies (Blue and Jensen, 1988; Bruschi et al., 2003; McCarthy and Mason-Gamer,
334 2019) by sampling leaves of a common age / developmental stage, in the same position on the
335 twig, and from twigs with comparable positions on the plants. Second, simulating alternative
336 sampling strategies will help maximize the ability to distinguish among populations, given
337 limited time and resources. Researchers can use preliminary data to simulate alternative
338 sampling strategies and estimate their power will be to distinguish populations under different
339 scenarios. The tools we developed for this study require only a matrix of traits and assignment of
340 those traits to populations and individuals to perform the simulations we describe above. We
341 expect that their use will facilitate planning of sampling designs for similar projects.

342 ***Leaf size, lobing, and SLA are predicted by latitude***— The measurements for each of our
343 leaves were well predicted by their latitude of origin: leaves were thicker, larger, and had deeper
344 lobes at southern latitudes, where leaves are exposed to warmer temperatures and higher
345 precipitation, and have longer growing seasons; and leaves were smaller, thinner, and had
346 shallower lobes at northern latitudes, where cold temperatures reduce water stress. This is in line
347 with previous studies demonstrating that leaf area covaries positively with temperature (Moles et
348 al., 2014; Wright et al., 2017) while SLA covaries negatively (Moles et al., 2014), and that leaf
349 circularity tends to increase in northern or cooler environments (Halloy and Mark, 1996;
350 Schmerler et al., 2012). Our results also parallel previous work in *Quercus ilex*, which exhibited
351 a similar leaf size gradient from north to south in the western Mediterranean basin, where
352 southern regions were likewise warmer and had higher amounts of precipitation than northern
353 regions (García-Nogales et al., 2016).

354 Our findings suggest a possible compensatory relationship between larger size and lobing
355 in bur oak. Community-level studies tend to show a higher frequency of lobed leaves in cooler
356 temperatures (Royer et al., 2005). These responses are individualistic, however, and among-
357 population responses in some species show no response or greater lobing in warmer temperatures
358 (Royer et al., 2008; McKee and Royer, 2017; McKee et al., 2019). Leaves that are deeply lobed
359 may be better adapted to warmer climates, because deeply lobed and narrow leaves have a
360 thinner leaf boundary layer, facilitating more rapid cooling (Givnish, 1987; McDonald et al.,
361 2003). In our study, the ratio of sinus depth to leaf width (sinus.v.width) shows a weak negative
362 correlation with latitude ($b = 0.013$, $P = 0.024$), but this result is strongly affected by one site,
363 Red Rock Canyon, which had an exceptionally low value. When this outlier is removed, the
364 correlation is no longer significant ($b = 0.007$, $P = 0.054$). In multiple regressions with scaled

365 data and bladeL as a covariate, however, depth of the sinus immediately above the deepest sinus
366 (sinusNextL) was significantly influenced by latitude ($b = 0.893$, $P = 0.021$), even with the
367 outlier removed ($b = 0.926$, $P = 0.023$). Our whole-leaf estimates of shape (circularity and
368 Haralick circularity) similarly both showed increased circularity northward, but their sensitivity
369 to the latitudinal gradient is different. This may be a consequence to the relative insensitivity of
370 Haralick circularity to leaf tooting (Haralick, 1974), which manifests in bur oak as differences
371 in crenulation. We did not quantify this effect directly, but leave it to future studies.

372 The hypothesis that leaf lobing increases southward in response to increased water stress
373 is supported by the specific leaf area (SLA) data. With leaf length as a covariate, SLA increases
374 northward ($b = 0.987$, $P = 0.011$), even as leaf size decreases. Leaves that are low in SLA have
375 higher water use efficiency (Mooney and Dunn, 1970; Marron et al., 2003; Liu et al., 2017) and
376 have been shown to vary within oaks according to water stress (Ramírez-Valiente and Cavender-
377 Bares, 2017; Ramírez-Valiente et al., 2017). This corresponds with our finding that bur oak
378 leaves at southern sites, where trees are exposed to warmer temperatures and are likely more
379 water-stressed, had significantly lower SLA than leaves collected at northern sites. However, leaf
380 area in cross-species oak comparisons covaries with SLA (Ramírez-Valiente et al., 2020), and
381 leaf area and SLA both decrease on average with increased water stress in cross-species
382 comparisons (Kaproth and Cavender-Bares, 2016; Ramírez-Valiente et al., 2020). Our finding
383 of larger leaf areas with lower SLA in bur oak, but with an increase in lobing, suggests that leaf
384 lobing may compensate for increased size in areas with great water stress.

385 The immense success of oaks (*Quercus*) in the Americas (Rodríguez-Correa et al., 2015;
386 Hipp et al., 2018; Cavender-Bares, 2019) has been attributed in part to oaks' ability to cross the
387 temperate-tropical divide. Bur oak is exceptional in its climatic range, extending from near the

388 boreal zone in the north to the great plains and the humid subtropics. Our finding that leaf lobing,
389 SLA, and leaf size compensate for one another along climatic gradients in bur oak may be
390 echoed in other species. The work presented here consequently has the potential to inform
391 studies of adaptive variation across oaks and temperate tree species more generally.

392

393 **ACKNOWLEDGMENTS**

394 This study was funded by The Morton Arboretum Center for Tree Science and USDA
395 Project 8020-21000-070-03S, a non-assistance cooperative agreement between U.S. National
396 Arboretum and The Morton Arboretum. We would like to thank Marlene Hahn for assisting with
397 curation of herbarium and leaf samples and Matthew Kaproth for advice on measurement of
398 SLA. Ricardo Kriebel provided particularly detailed advice on morphometric analysis, including
399 code to assist in generating landmarks and excellent feedback on interpretation of our results;
400 and Associate Editor Dylan Schwilk, with an anonymous reviewer and Kriebel, provided
401 editorial feedback that substantially improved the manuscript.

402

403 **AUTHOR CONTRIBUTIONS**

404 A.L.H., A.T.W. and S.C.D. conceptualized and designed the project. S.C.D., M.G., and
405 S.F. collected specimens and data. S.C.D. and A.L.H. conducted data analyses. S.C.D. wrote the
406 first draft of the manuscript, and A.L.H. revised the manuscript in response to reviewers. A.L.H.
407 coded and analyzed simulations and contributed to data analysis. All authors contributed to
408 writing and revisions; A.L.H. and S.C.D. contributed equally to analysis and writing.

409

410 **DATA ACCESSIBILITY**

411 Data and scripts used to conduct the statistical analysis are archived in GitHub
412 (<https://github.com/andrew-hipp/oak-morph-2020>) and released through Zenodo
413 (<https://doi.org/10.5281/zenodo.4213821>). Supplemental figures are available in the GitHub
414 repository and in the online Supplement.

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- 610

611 **Table 1. Sampling localities, Bioclim values for each site, number of leaves collected per**
 612 **tree.** Only leaves used for statistical analysis are counted. Broken or incomplete leaves were
 613 eliminated from statistical analysis. Abbreviations: Bio1 = mean annual temperature (in degrees
 614 C); Bio12 = mean annual precipitation (in mm).

<u>Site</u>	<u>Bio1, Bio12</u>	<u>Tree</u>	<u>Latitude</u>	<u>Longitude</u>	<u>Lvs</u>
Whiteshell Provincial Park	2.07°C, 566 mm	MB-SD004	49.4249	-95.1436	8
		MB-SD005	49.71279	-95.2444	8
		MB-MG513	49.71209	-95.24496	8
Spruce Woods Provincial Park	2.50°C, 460 mm	MB-MG516	49.76104	-99.15971	8
		MB-MG517	49.76095	-99.15983	8
		MB-MG518	49.76061	-99.15928	8
Assiniboine Forest	2.10°C, 519 mm	MB-MG528	49.85778	-97.24848	8
		MB-MG529	49.85423	-97.2482	8
		MB-MG530	49.85392	-97.24828	8
University of Minnesota Campus	7.10°C, 738 mm	MN-MG788	44.97882	-93.23768	8
		MN-MG789	44.97739	-93.23761	8
		MN-MG790	44.97771	-93.23801	7
Cherokee Park Trail	9.20°C, 879 mm	IA-MG243	41.97454	-91.72161	8
		IA-MG244	41.97367	-91.72547	8
		IA-MG245	41.97362	-91.72565	6
Morton Arboretum	9.50°C, 932 mm	IL-SF001	41.81696	-88.0808	8
		IL-SF002	41.81331	-88.08266	8
		IL-SF003	41.81588	-88.07994	8
Prairie Moon Nursery	6.80°C, 837 mm	MN-SD001	43.89117	-91.64684	8
		MN-SD002	43.89804	-91.648	8
		MN-SD003	43.89088	-91.64689	2
Burr Oak Woods	9.80°C, 943 mm	IN-MG631	41.53273	-87.2948	8
		IN-MG636	41.5345	-87.29279	8
		IN-MG638	41.53253	-87.29661	8
Red Rock Canyon State Park	15.3°C, 756 mm	OK-MG369	35.43874	-98.35495	8
		OK-MG370	35.43851	-98.35503	8
		OK-MG371	35.43854	-98.35497	8
Mohawk Park	15.3°C, 987	OK-MG347	36.21066	-95.89467	8

	mm	OK-MG349	36.2204	-95.89845	8
		OK-MG350	36.22064	-95.89877	8
Tallgrass Prairie Preserve	14.3°C, 939 mm	OK-MG282	36.84504	-96.42526	8
		OK-MG283	36.84485	-96.42479	2
		OK-MG284	36.84501	-96.42553	3
Buttin Rock Access	13.1°C, 1121 mm	MO-MG402	37.15687	-91.36471	8
		MO-MG403	37.15686	-91.36501	8
		MO-MG404	37.15726	-91.36518	8

615

616 **Table 2. Descriptions of the leaf traits measured**

<u>Leaf measurements</u>		
Trait	Abbreviation	Definition
Blade length (mm)	bladeL	Straight line distance measured from intersection of leaf and petiole to tip of the leaf at its point of intersection with the midvein
Blade width (mm)	bladeW	The longest possible perpendicular line drawn from one edge of the blade to the other; vein position used to identify the leaves opposite one another
Width of blade between deepest pair of sinuses (mm)	sinusMinL	The shortest distance that separates the deepest sinus from its corresponding sinus. (The deepest sinus is defined as the sinus that has the longest distance from the most interior point of the sinus to the line that connects the two most exterior points of that sinus)
Width of blade between sinuses just above the deepest pair (mm)	sinusNextL	The width between the sinuses that are immediately distal to the deepest sinuses (as defined in sinusMinL)
Petiole length (mm)	petioleL	Measured from the base of the blade as defined by bladeL to the base of the petiole, defined as the line of intersection between petiole and branch, upper surface of the petiole
Petiole width (mm)	petioleW	Measured at the point of intersection between the blade and the petiole, where blade is not visible
Length of lamina from base to widest point (mm)	bladeLtoWidestPoint	Measured from the base of the blade to the point of intersection between the midvein and the line used to measure leaf blade width
Blade base angle (degrees)	bladeBaseAngle	Measured using the lines that define the widest angle between the base and either edge of the leaf
Total length (mm)	BL.PL	Total length is the blade length added to the petiole length
Leaf area (mm ²)	Area	Calculated in imageJ.

Ratios

Petiole length / Total length	PL.TL	The petiole length divided by the total length
Sinus ratio	SinusRatio	The width of the blade between the deepest pair of sinuses divided by the width of the blade between the pair of sinuses just above the deepest pair
Blade length/ Blade width	BL.BW	The blade length divided by the blade width
Petiole length / Petiole width	PL.PW	The petiole length divided by the petiole width
Blade length / Blade length to widest point	BL.BLWP	The blade length divided by the length of the blade from the base to the widest point
Ratio of Leaf size to petiole length	BL.BW.over.PL.PW	The blade length divided by the blade width divided by the petiole length divided by the petiole width
Specific leaf area	SLA	Leaf area divided by the mass of the leaf
Lobedness	sinus.v.width	The width of the blade between the deepest pair of sinuses divided by the blade width

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620 **Table 3. Simple and multiple regressions for all leaf traits.** The columns for Blade length and
 621 Latitude represent the regression coefficient and p-value for a multiple regression with each leaf
 622 trait regressed against Blade length and Latitude. Note that after Bonferroni correction for
 623 multiple tests, only the regression of blade length on latitude + petiole width is significant; and
 624 for that multiple regression, only the coefficient for latitude is significant

Leaf trait	p-value	r^2	Blade length	Latitude	R^2
bladeL	0.012	0.486		-0.697, p = 0.012	0.486
bladeW	0.014	0.469	0.926, p < .001	-0.039, p = 0.780	0.911
sinusMinL	0.208	0.153	-0.069, p = 0.874	0.343, p = 0.443	0.156
sinusNextL	0.492	0.048	0.966, p = 0.014	0.893, p = 0.021	0.528
petioleL	0.262	0.124	0.812, p = 0.041	0.214, p = 0.546	0.463
petioleW	p < 0.001	0.692	0.119, p = 0.649	-0.749, p = 0.017	0.699
bladeLtoWidestPoint	0.011	0.494	0.920, p < .001	-0.062, p = 0.630	0.929
bladeBaseAngle	0.151	0.195	-0.363, p = 0.386	-0.695, p = 0.116	0.263
TotalL.PL.BL	0.019	0.438	1.03, p < 0.001	0.052, p = 0.459	0.979
Area	0.014	0.469	0.949, p < 0.001	-0.024, p = 0.847	0.933
SLA	0.015	0.466	0.438, p = 0.188	0.987, p = 0.011	0.564
PL.TL	0.945	$r^2 < 0.001$	0.347, p = 0.461	0.264, p = 0.572	0.062
SinusRatio	0.425	0.065	-0.253, p = 0.580	0.078, p = 0.864	0.098
BL.BW	0.313	0.101	-0.367, p = 0.408	0.062, p = 0.886	0.171
BL.BLWP	0.834	0.005	0.183, p = 0.699	0.196, p = 0.680	0.022
sinus.v.width	0.024	0.415	-0.551, p = 0.103	0.259, p = 0.415	0.571
sinus.v.width (no spruce woods)	0.054	0.352	-0.296, p = 0.152	0.163, p = 0.391	0.507

625

626

627 **Table 4. ANOVA for bladeL, SLA, PC1, PC2**

Response		Df	Sum of Squares	Mean Square	F-value	Pr(>F)
bladeL	site	11	177345	16122.3	38.9996	< 2.2e-16
	tree	24	83159	3465.0	8.3817	< 2.2e-16
	residuals	236	97562	413.4		
SLA	site	11	1017054857	92459532	30.3766	< 2.2e-16
	tree	24	703085034	29295210	9.6246	< 2.2e-16
	residuals	236	718331913	3043779		
PC1	site	11	984.70	89.519	41.7620	<2.2e-16
	tree	24	300.10	12.504	5.8335	8.101e-14
	residuals	236	505.88	2.144		
PC2	site	11	400.34	36.394	34.042	<2.2e-16
	tree	24	318.70	13.279	12.421	<2.2e-16
	residuals	236	252.30	1.069		

628

629

630

631 **FIGURE LEGENDS**

632

633 Figure 1. Locations of sampling sites for this study as well as mean annual temperature across
634 the bur oak range. WorldClim temperature data are scaled to a factor of 10. Specific information
635 about site, name, location, and number of samples collected can be found in Table 1.

636

637 Figure 2. Leaf trait measurements used in this study. All measurements used in this study were
638 linear measurements or ratios of linear measurements, plus one angle. Details and definitions are
639 found in Table 4.

640

641 Figure 3. Simple regressions of traits and environment that are significant at the 0.05 level. P-
642 values are not corrected for multiple tests; a total of seventeen regressions were performed
643 (Table 3).

644

645 Figure 4. Simple regressions of circularity on latitude.

646

647 Figure 5. Regressions of bioclim variables on latitude. Latitude shows up as the strongest single
648 predictor of leaf morphology in the current study, as it integrates over both day length and
649 several aspects of climate: bio 1 (mean annual temperature), bio 12 (mean annual precipitation),
650 bio 4 (mean temperature seasonality).

651

652 Figure 6. Sampling simulations. Simulated sampling strategies accounted for covariance among
653 traits within leaves; among leaves on trees within sites; and among trees within sites. Here, two
654 estimates of power are reported: the number of groups of sites recognized as distinct from each
655 other using Tukey's HSD at $\alpha = 0.05$; and the probability of recognizing at least 50% of sites as
656 distinct from each other. colors scale from darker as a higher number of groups are recognized,
657 lighter as fewer are. Simulated numbers of sites distinguished (left panel) and probabilities of
658 distinguishing at least 50% of simulated sites (right panel) are reported in each cell of the
659 simulation.

660

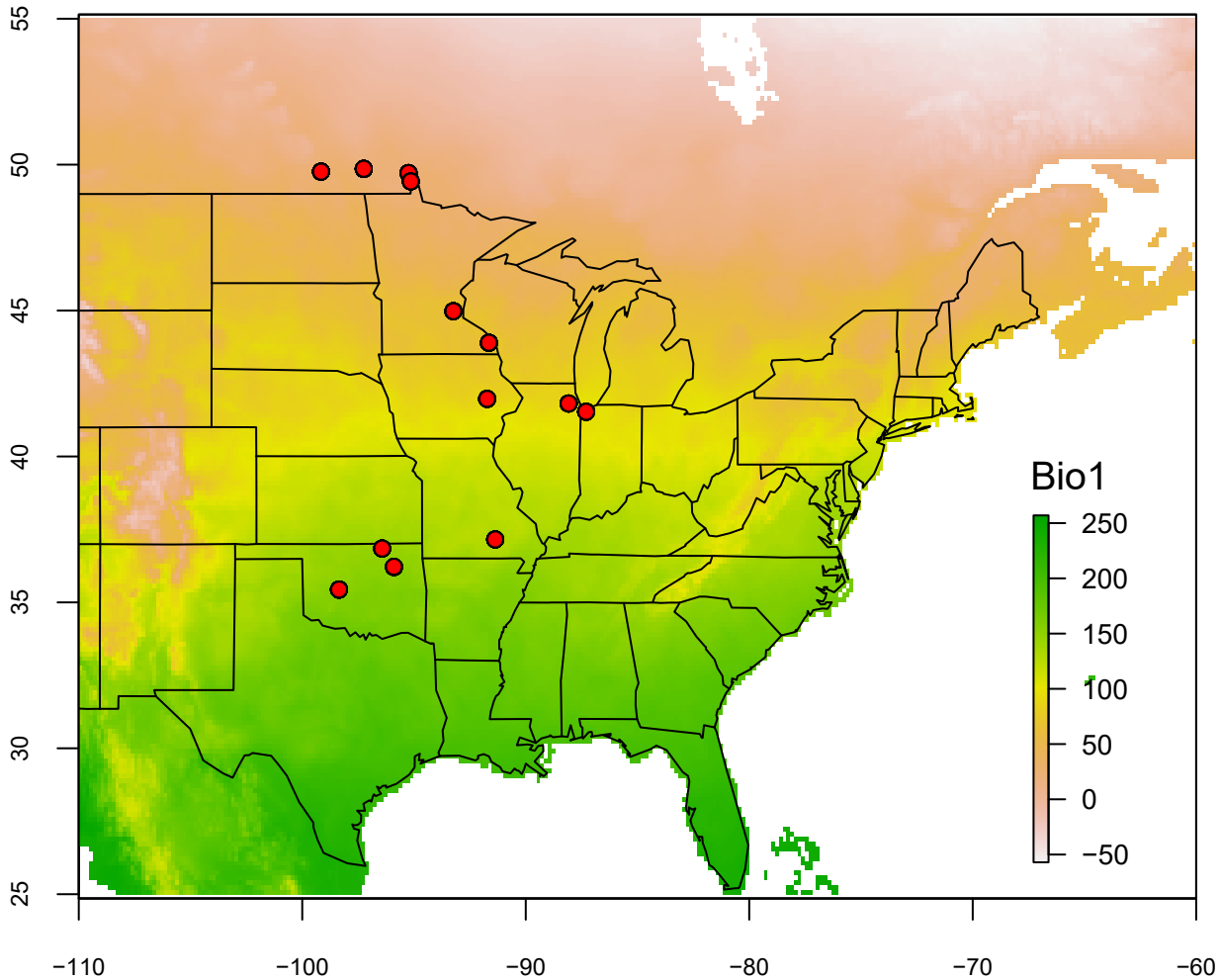
661 Supplemental Figure S1. Biplots of all simple regressions performed, whether significant or not

662 Supplemental Figure S2. PCA based on eFourier analysis of leaf outlines.

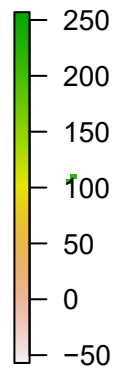
663 Supplemental Figure S3. Non-metric multidimensional scaling ordination of PCA on leaf

664 measurements

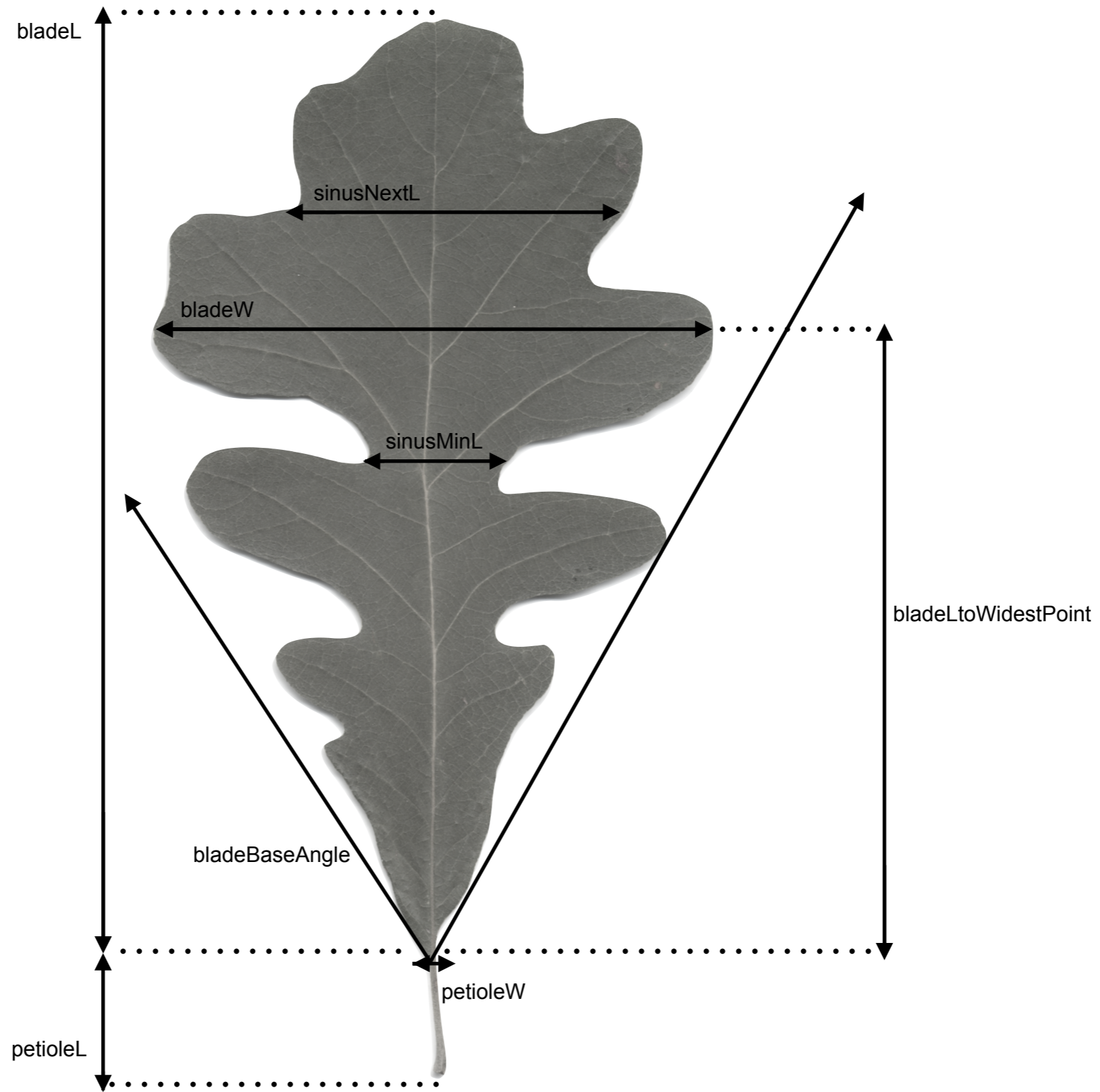
Latitude (degrees)

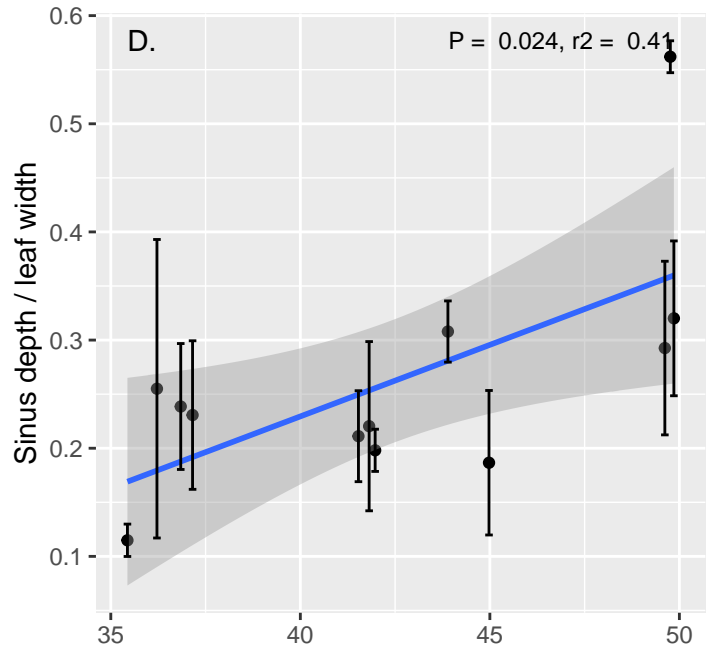
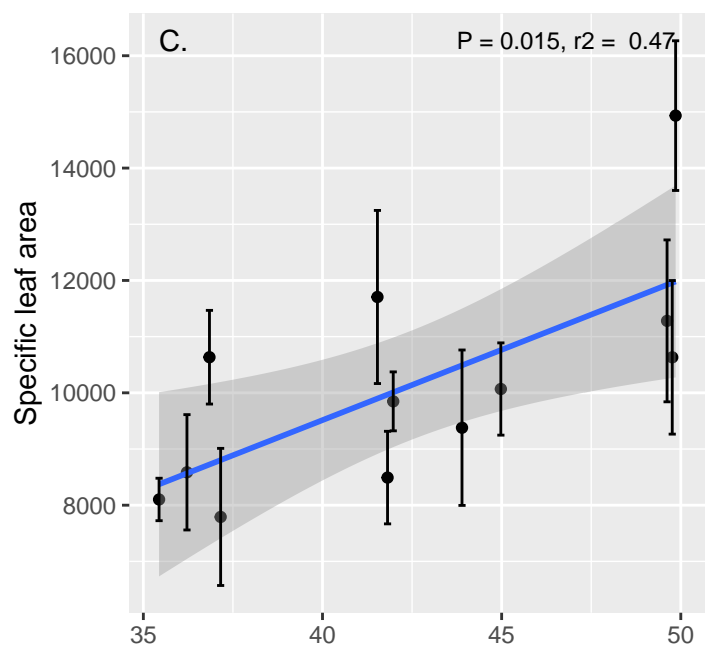
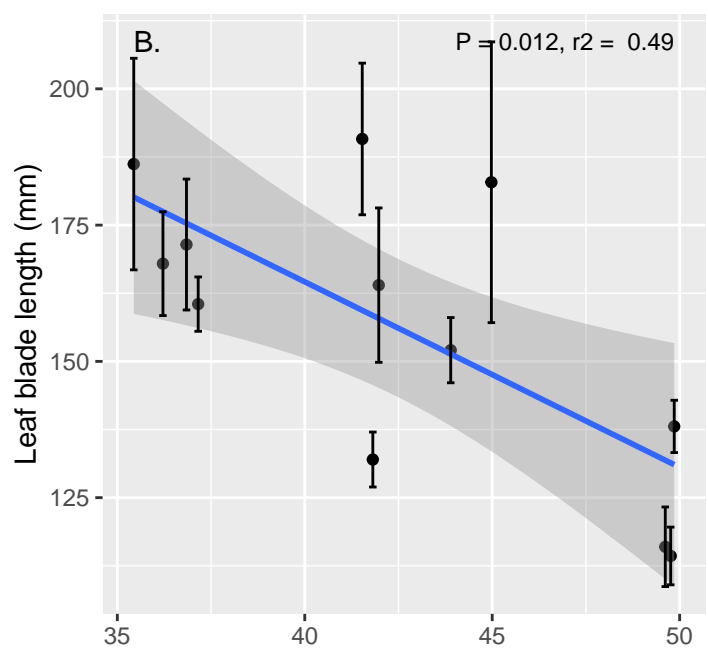
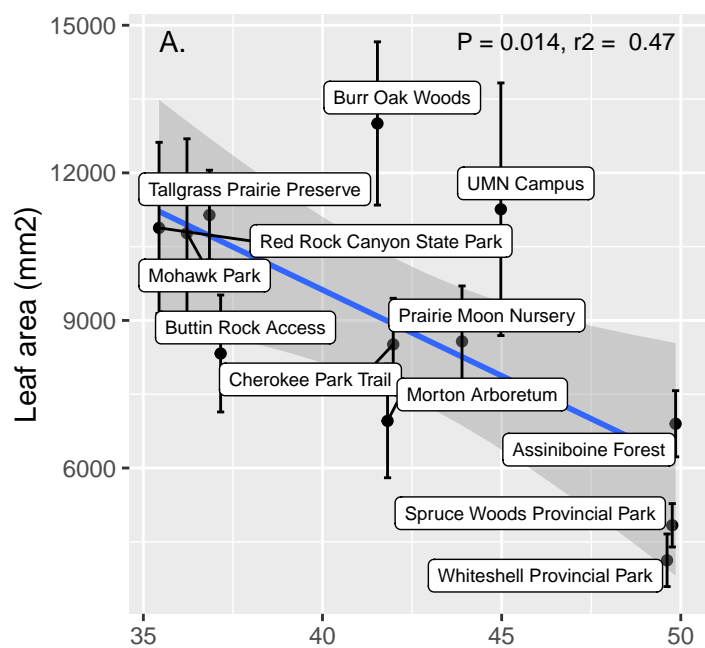


Bio1

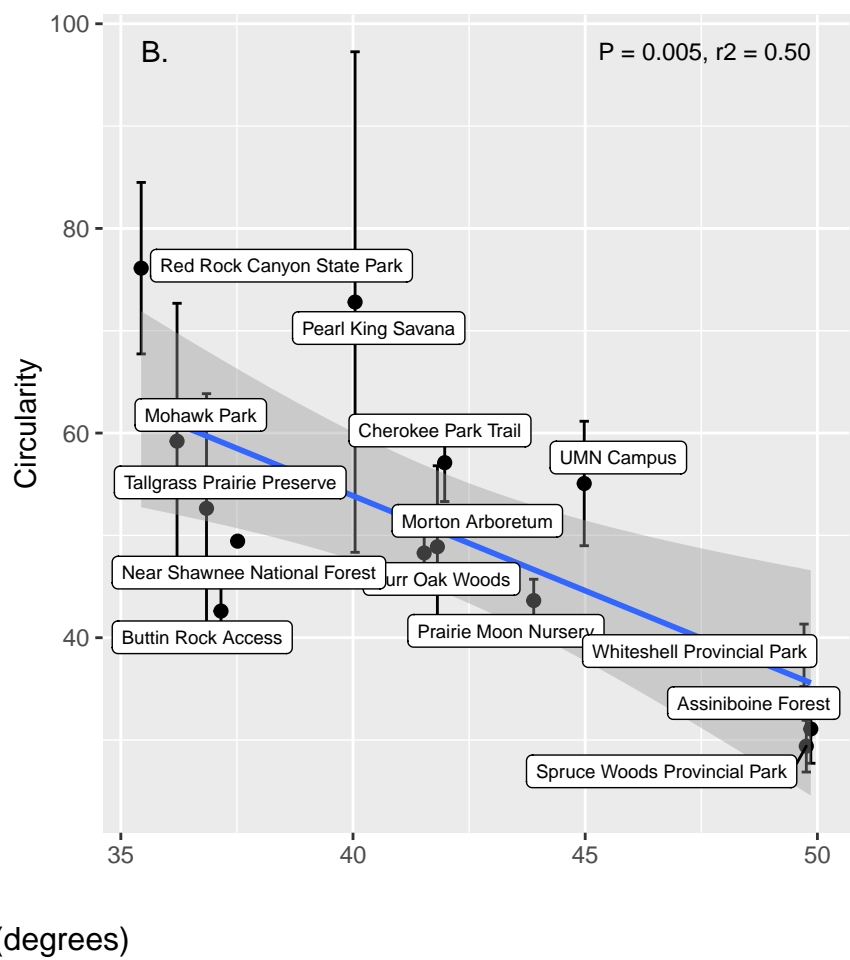
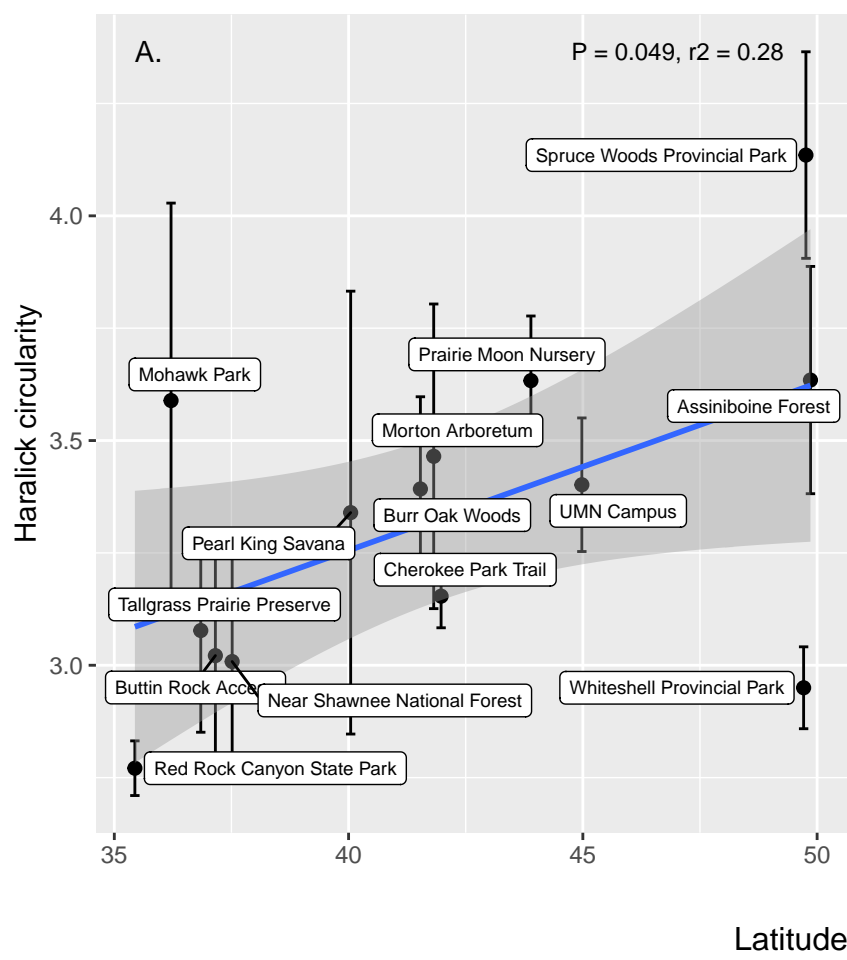


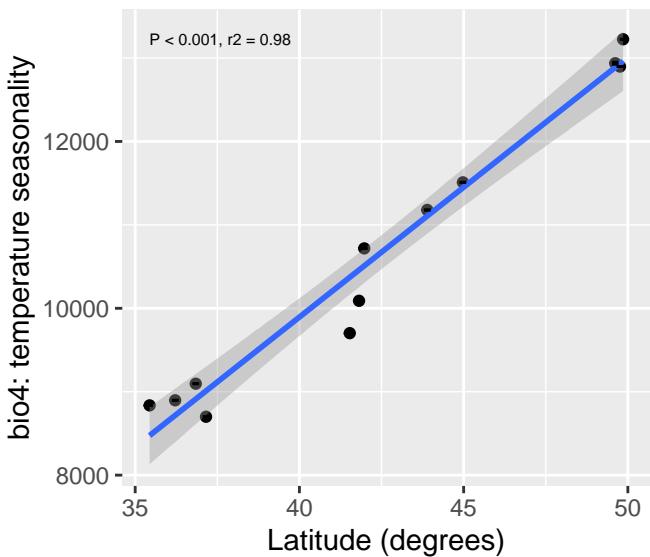
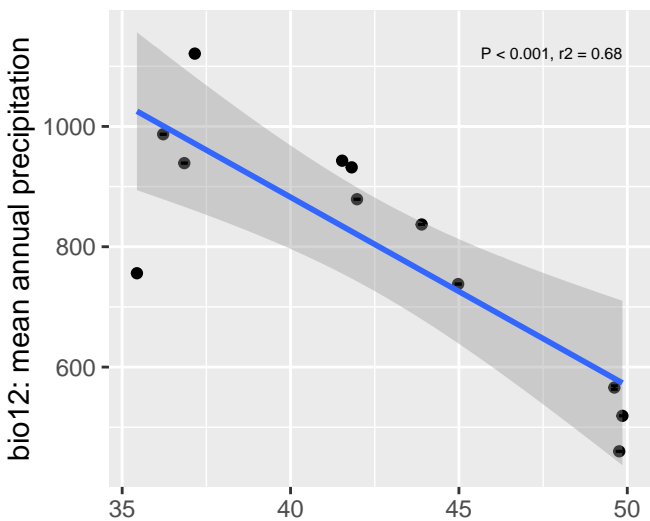
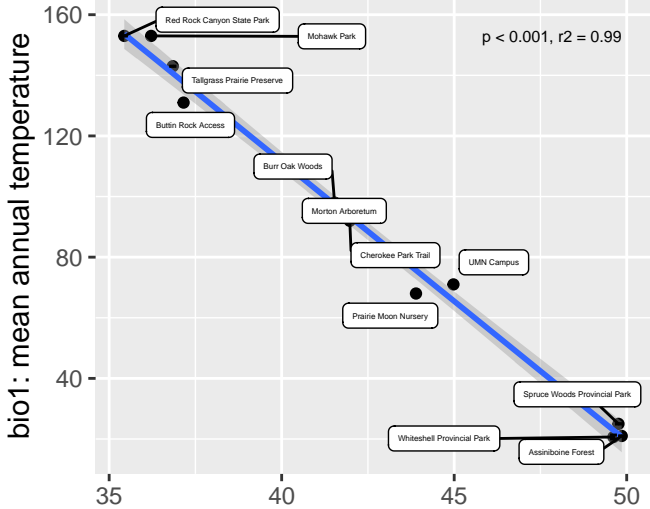
Longitude (degrees)



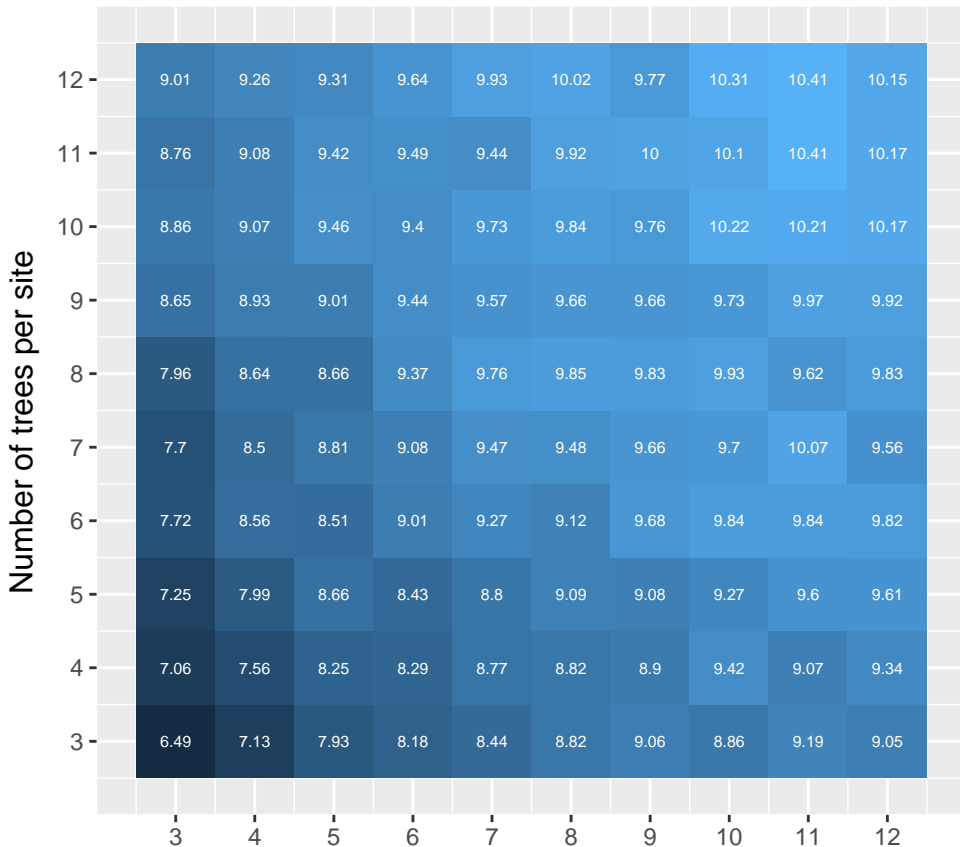


Latitude (degrees, all plots)

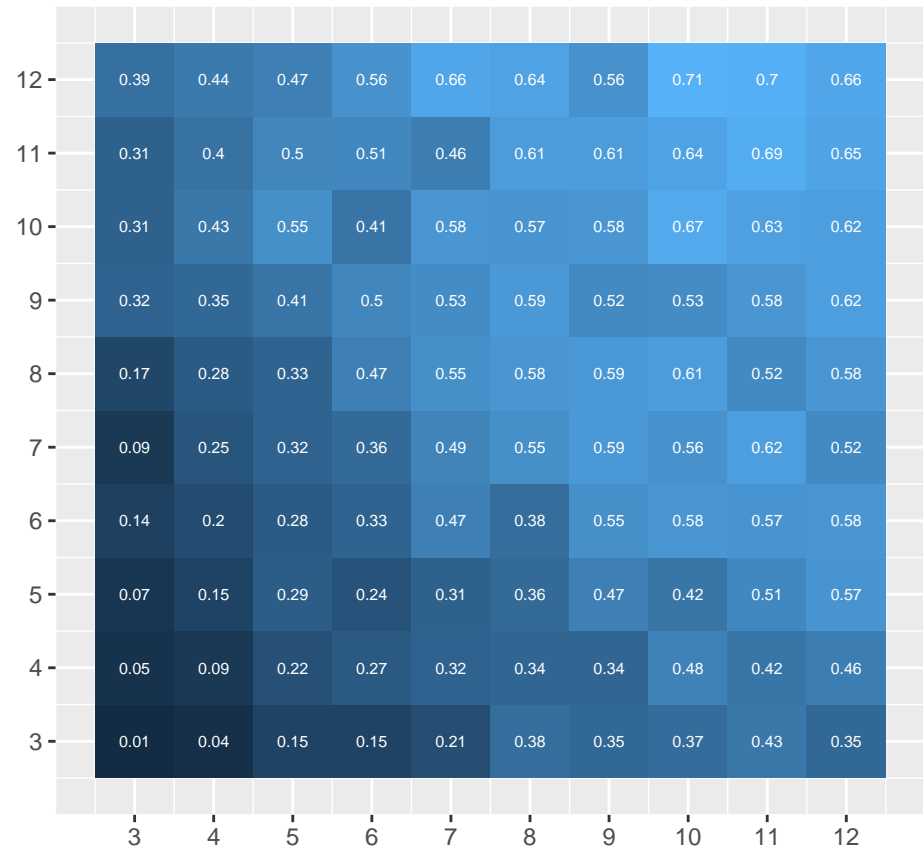




Mean groups recognized out of 20 populations



Probability of recognizing 50 percent of populations



Number of leaves per tree