

1 **Variability, drivers, and utility of genetic diversity-area relationships in**
2 **terrestrial vertebrates**

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20

21 **Abstract**

22 Maintaining genetic diversity within and among populations is critical for conservation and a
23 prominent goal of the Kunming-Montreal Global Biodiversity Framework. However, direct
24 estimates of genetic diversity are unavailable for most species, and time and resources are
25 insufficient to fill these substantial data gaps and meet conservation target timelines. Robust,
26 proxy-based predictions of genetic diversity loss would therefore be valuable for conserving
27 genetic diversity for the many species lacking DNA-based data. We evaluated one such
28 approach, the Genetic Diversity Area Relationship (GDAR), which describes the relationship
29 between genetic diversity and the geographic area occupied by a species. We estimated
30 differences in genetic diversity relative to the size of sample area using 55 previously published
31 datasets from 51 species and found that GDARs were highly variable across species and strongly
32 dependent on population structure. The mean change in allele count relative to area sampled
33 across all species did not predict genetic diversity differences for individual species well. Traits
34 correlated with population structure explained little variation in the GDAR. Our findings suggest
35 that using a single GDAR is not appropriate to predict genetic diversity loss for individual
36 species following area loss. Further work is needed to identify accurate methods to estimate
37 species-specific levels of genetic diversity decline with area without genetic data. Although the
38 GDAR remains valuable to highlight likely global patterns and scales of genetic diversity loss
39 across many species, our results suggest it is currently too inaccurate for species-specific use.

40 **Keywords:** species-area relationship, F_{ST} , population differentiation, conservation,
41 macrogenetics, vertebrates, biodiversity, zMAR, genetic indicators

42 **Introduction**

43 Genetic diversity is a fundamental component of biodiversity that is critical for the long-term
44 resilience of populations and species^{1,2}. Parties to the Convention on Biological Diversity
45 formally committed to conserving genetic diversity and to measuring the progress toward this
46 goal in 2022 with the signing of Kunming-Montreal Global Biodiversity Framework³ (“KM
47 GBF” Goal A, Target 4⁴). However, monitoring genetic diversity change is difficult and has been
48 neglected due to cost, expertise barriers in data production, and difficulties in sample collection.
49 Consequently, we do not have sufficient genetic data for the assessment and monitoring of most
50 species⁵, and the substantial resources needed for direct genetic assessments of species at the
51 global scale are not on the horizon⁶. With the necessarily ambitious KM GBF target of halting
52 the loss of genetic diversity and restoring conditions to support adaptive capacity by 2030,
53 approximations or indicators of genetic diversity are urgently needed to support genetic diversity
54 monitoring and conservation.

55

56 *Diversity-area relationships from species to alleles*

57 Genetic diversity change could potentially be approximated by extending the concept of species-
58 area relationships (SAR) to genetic diversity^{7,8}. The SAR is a simple, widely-used relationship in
59 conservation that describes how species richness decreases from larger toward progressively
60 smaller areas⁹⁻¹¹. For conservation purposes, the SAR has been used to approximate changes in
61 species richness across regions differing in amounts of habitat over space and time. Applying the
62 SAR at a genetic level could similarly be a shorthand for gauging genetic diversity loss as habitat
63 and range size shrink^{7,8}.

64 The traditional simple power law formulation of the SAR is: $\log(S) = \log(c) + z * \log(A)$, where
65 S is the number of species in a region with area A , c is a constant, and the exponent z
66 characterizes the linear rate of increase in species number with area. Different approaches for
67 characterizing SARs exist¹²; a traditional one is that of a nested design (Fig. 1), where
68 consecutively larger surrounding areas are assessed to estimate the rate at which the number of
69 species sampled increases.

70 The generalizability of SARs across different ecological settings has been well studied, and the
71 shape of the SAR relationship, and thus its conservation utility, is variable and context-specific
72 (e.g., endemics area relationships¹³, countryside SAR¹⁴). The simplicity of the SAR and its direct
73 link to population size (approximated by area) and, thus, genetic drift, offers an intriguing
74 potential pathway for considering area effects on genetic diversity. Similar genetic diversity-
75 area relationships (GDARs) that hold across species would facilitate estimating and forecasting
76 genetic change for species whose ranges have shrunk and genetic data is unavailable or difficult
77 to collect. The expected mean losses of genetic variants as species ranges shrink may be
78 predictable in a way similar to the power-law SAR^{7,8}.

79

80 If an accurate, reliable GDAR existed and held for spatial and temporal differences in area,
81 predicting genetic diversity loss in a given species would require only knowledge of the area of a
82 species range that has been lost, and the corresponding change in numbers of alleles (z values in
83 the SAR formula). This could allow managers to identify species and locations that have lost, or
84 might soon lose, significant amounts of genetic diversity due to habitat loss. The simplicity of
85 GDARs would make them powerful tools for managers and policymakers¹⁵. Overall, a GDAR
86 that held across species would vastly expand the scope of species and places where estimates of

87 genetic diversity loss could be considered in conservation practice, circumventing some of the
88 limitations surrounding genetic data collection.

89 Interest in applying the SAR concept to genetic diversity conservation is growing, including
90 proposals to explore whether average z values could suitably predict genetic diversity loss across
91 species⁸, or whether z values could be estimated separately for species with high versus low
92 population structure⁷. An exploration of power law relationships between genetic diversity and
93 area across 20 species, spanning plants, insects, birds, and mammals, suggested that a mean z
94 value of 0.3 (values ranged between 0.015—0.824) may be sufficient to capture general patterns
95 of change across species⁵.

96 However, the promise of the GDAR as a predictor of genetic diversity change relative to area has
97 not been fully evaluated. Specifically, forecasting is defined by the slope of the GDAR (z),
98 however we do not yet know the extent to which z values can be generalized or predicted across
99 species. Genetic diversity declines up to 10% by 2030 may lead to harmful increases in
100 inbreeding and loss of fitness in wild populations¹⁶. With small margins of error for genetic
101 diversity loss, robust forecasting is key.

102

103 *Spatial structure in diversity-area relationships*

104 Genetic diversity is not distributed evenly across species ranges¹⁷. The null expectation is that
105 populations are structured by isolation by distance due to the tendency of individuals to mate
106 with others close by¹⁸. Population genetic structure is sometimes related to, and therefore may be
107 well-predicted by, ecological attributes of species^{19,20} and landscapes^{21,22}. For example, we might
108 generally predict that flying, wide-ranging generalist species, such as some bats, would tend to

109 have a more uniform spatial distribution of alleles (and less genetically structured populations)
110 because individuals are highly mobile and have higher dispersal capacities, increasing gene flow
111 among populations²³. Alleles would be lost at a relatively constant rate with area (Fig. 1c). We
112 would in turn predict that species with low dispersal capacities and patchy habitat distributions,
113 such as salamanders, would tend to have more clustered distributions of alleles and well-defined
114 genetic population structure due to lower rates of gene flow among populations²³. Such species
115 could rapidly lose genetic diversity as larger areas that encompass multiple distinct populations
116 are lost (Fig 1c). The change in the number of alleles across spatial scales (z) should therefore
117 depend directly upon the degree to which populations are spatially structured, which in turn is
118 influenced by the landscape, species traits, biogeography, and demographic histories^{7,23,24}.

119 Drivers of the GDAR z should thus be associated with measures of population genetic structure.
120 In SARs, the direct link between z and the spatial turnover of species (or portion of species
121 shared between a larger and a nested smaller area—i.e., beta diversity) is well-known^{25,26}. For
122 specific sampling design cases and geographic range distributions, the connection is
123 mathematically defined^{27,28}, and accounting for these beta diversity estimates fully determines z
124 values and vice versa. Given biogeography's historical development and the more direct
125 conservation applications, z values and SAR have seen greater popularity as a research focus
126 than beta diversity. This differs from population genetics, where beta diversity describes spatial
127 genetic structure¹⁸. The fixation index, F_{ST} , is a standard measure of allele frequency variation
128 that is attributable to population genetic structure that has very well-understood theoretical
129 underpinnings^{29,30}. In its simplest form²⁹, F_{ST} can be estimated as $(H_T - H_S)/H_T$, where H_T is the
130 heterozygosity of the total population without considering subpopulation structure, H_S is the

131 average heterozygosity of subpopulations, and the difference between the total and average
132 heterozygosity of subpopulations is standardized by total population-level heterozygosity.
133 As with the SAR, it is likely that the exponent z in the GDAR is a measure of beta diversity at
134 the genetic level, and is thus strongly correlated with F_{ST} . Given our strong theoretical
135 understanding of F_{ST} , assessing its empirical connection to GDAR z values has the potential to
136 link newly emerging perspectives related to GDARs with population genetics to advance
137 conservation. By repurposing publicly available microsatellite genetic datasets from wild
138 populations, we expand the number of terrestrial vertebrates with empirically derived GDARs to
139 51 species and assess the empirical variability in GDAR z values. Finally, we test putative
140 drivers of z and F_{ST} to explore whether ecological predictors would support a straightforward use
141 of GDARs by conservation practitioners. If GDAR z values were either reasonably similar
142 among species or if their variation were well-captured and predictable, an opportunity would
143 exist for employing the GDAR relationship to predict genetic diversity change for individual
144 threatened species, rather than just at a global or regional level, helping conservation
145 prioritization.

146

147 **Results and Discussion**

148 *Variation in genetic diversity area relationships*

149 The GDAR can be estimated identically to the SAR by considering alleles as species. We
150 artificially sampled each genetic dataset using a nested GDAR design (sampling concentric areas
151 of increasing size) and estimated z values as the slope of the log-log relationship between the
152 number of alleles sampled and the size of the area from which they were sampled (Fig. 1; see

153 Methods). We first highlight two examples, the little brown bat (*Myotis lucifugus*) and the Mount
154 Lyell salamander (*Hydromantes platycephalus*), that illustrate how GDAR shapes can vary
155 substantially with movement ability (Fig 1C). Due to its flight ability, we predicted that the little
156 brown bat should exhibit less population structure than a comparatively less vagile salamander
157 species due to higher possibility of gene flow. These contrasting population structures should
158 shape the GDAR, with the more structured Mount Lyell salamander losing alleles more quickly
159 as area is lost than the genetically well-mixed little brown bats. Indeed, estimates of z for these
160 two species are very different (Fig 1c).

161 This considerable variation in the shape and strength of GDARs extends across the 51 terrestrial
162 vertebrate species we assessed (Fig. 2, Tables S1, S2). Generally, the number of alleles was
163 positively correlated with the size of the geographical area sampled, which explained a
164 substantial proportion of variation in allele count (mean $R^2 = 63\%$ across datasets, Fig. S2). Z
165 values ranged from 0.05 to 0.27 (mean 0.12), with amphibians and reptiles exhibiting the largest
166 range of values.

167 Allele count is highly sample size dependent, so we also assessed two alternative, commonly
168 used metrics of genetic diversity that are less sensitive to sample size differences³¹: allelic
169 richness, standardized using rarefaction and thus comparable counts of alleles across different
170 sample sizes, and gene diversity³², the average probability that two randomly sampled alleles are
171 different in a nonrandom mating population. For both metrics, nearly all datasets showed
172 significant area dependence, but with generally much shallower and statistically weaker
173 relationships than those of allele count (mean R^2 allelic richness = 32%, gene diversity: 24%;
174 Fig. 2, Table S1, Fig. S2). This confirms the important role of sample size in driving GDAR

175 patterns based on counts of alleles. Mean z values did not strongly vary across terrestrial
176 vertebrate classes for any genetic metric (Table S2).

177

178 *The slope of the GDAR approximates population structure*

179 We estimated F_{ST} for each genetic dataset to quantify population genetic structure and assessed
180 its role in explaining GDARs. In a hierarchical regression model combining data across all
181 species, we found population structure interacted substantially with area to explain the rate of
182 genetic diversity change with reduced area sampled (Fig. 3, Table S3). Specifically, species with
183 more population structure (higher F_{ST}) lost alleles more rapidly when sampling smaller and
184 smaller geographic areas. For allelic richness and gene diversity, the effect of sample area was
185 negligible when population structure was statistically held at zero, and it was an order of
186 magnitude smaller than in a model with area alone (Fig. 3, Table S3). For allele count, the metric
187 most affected by sample size, the effect of area was similar in both models, but the interaction
188 effect was stronger (Fig. 3, Table S3). These results demonstrate that population structure sets
189 the shape of GDARs and, ultimately, the initial change in genetic diversity following area loss.
190 Across species, z was consistently strongly correlated with F_{ST} for allele count, allelic richness,
191 and gene diversity (Pearson $r_{\text{allele count}} = 0.69$ [0.53 - 0.80, 95% CI], $r_{\text{allelic richness}} = 0.94$ [0.90 -
192 0.96]; $r_{\text{gene diversity}} = 0.98$ [0.96 - 0.99]; Fig. 3).

193

194 *The predictive potential of GDARs for conservation*

195 We next assessed the extent to which z values could predict the area-dependence of genetic
196 diversity across species. Average z values based upon all species did not yield robust predictions

197 of diversity differences in individual species with a slight tendency to overpredict (Fig 4). While
198 z values derived from the data necessarily predicted average differences well, they poorly
199 predicted differences in specific regions within the study area (Fig. 4b). Together, these results
200 suggest that while GDARs may be promising tools for predicting the area-dependence of genetic
201 diversity in aggregate across large numbers of species, they may not be suitable for predicting
202 genetic diversity change for any given single species. Similarly, z values for species are likely
203 not informative for predicting genetic diversity change for specific regions within the species
204 range without prior knowledge of spatial genetic diversity patterns.

205

206 *Ecological predictors of population structure and GDAR*

207 Given the existence of species-level correlates of population structure, it may be possible to
208 roughly infer z values for GDARs from species traits. We thus tested the extent to which we
209 could predict F_{ST} and z from readily available trait data for 33 mammal species. We used three
210 traits related to the spatial distribution of individuals that likely affect population structure: body
211 size, home range size, and geographic range size. We included the total sampling area of each
212 study as an additional predictor. Together, these variables explained approximately half of the
213 variation in species' global F_{ST} (52%) and less than half of the variation in z values (38 – 42%
214 across genetic metrics; Table S4). Partitioning the data into training and test sets, the average
215 relative prediction error was nearly 60% for F_{ST} predictions (mean coefficient of variation [CV]
216 = 0.56), and similar for z_{GD} (0.66) and z_{AR} (0.59). Error was lower for allele count-derived z_{AC}
217 predictions (CV = 0.27). Finally, we tested the capacity of this model to predict F_{ST} in 36 species
218 from an independently collected literature-based dataset containing microsatellite F_{ST} values,
219 MacroPopGen^{33,34}, and found predictive capacity was poor (CV = 1.05).

220 These results suggest that without genetic data, approximating z based on traits or other data is
221 not straightforward. Given the low predictive capacity of our models when assessed on the data
222 the models were fit with, it is unsurprising that the models also poorly predicted new data from
223 the literature-compiled MacroPopGen data set. Another reason for low predictability across both
224 datasets is that most species samples were not range-wide, as in previous work⁸. Haphazardly
225 sampling regional structure may yield more idiosyncratic results than whole-species population
226 structure, adding statistical noise when making predictions across species. This suggests that
227 high-quality training data are needed to predict F_{ST} or z values. However, these are not currently
228 available for most species⁵, which could significantly impact the applied use of this method.
229 Broader explorations of the relationship between global F_{ST} and z across species and ecological
230 and evolutionary contexts are needed to further assess the practical predictability of z in GDARs.

231

232 *Limitations and opportunities of using GDARs for conservation*

233 Our results affirm the existence of GDARs^{7,8} and expand our empirical understanding of GDAR
234 variation and the connection between GDARs and population genetics. However, even for the
235 relatively well-studied species in our analysis, the predictive ability of a broadly parameterized
236 GDAR, or single z value, is limited and its practical use for single-species conservation at this
237 time is doubtful.

238 Our work identifies other limitations and opportunities around further standardization and data
239 collection to support progress toward a more effective use of genetic data for conservation. A
240 standout issue is the very limited availability of genetic data. We used microsatellite data, which
241 remains widely used for wildlife studies—particularly for species lacking reference genomes.

242 However, all of the z values we estimated were below 0.3, the average z reported in Exposito-
243 Alonso et al.⁸, and below 0.25, the intermediate F_{ST} value proposed by Mimura et al.⁷. This is
244 likely due to differences in data types (SNPs versus microsatellites), dataset preparation (e.g.,
245 minor allele filtering in SNP datasets), data structure (individual vs. population-level sampling),
246 sampling extents (local to range-wide), and chosen diversity metrics. It is thus important to
247 consider that factors such as data type, sampling strategy, and diversity metrics affect estimated z
248 values and, thus, the magnitude of the estimated loss.

249 Finally, we note two more probable limitations of GDARs. First, genetic diversity loss depends
250 not only on the total area lost but on what *specific* areas are lost. In species with highly structured
251 populations, there are often hot and coldspots of genetic diversity throughout a range, and the
252 area occupied by hot and coldspots will vary¹⁷. Range contractions in low diversity areas (e.g. at
253 range edges, or sink populations) will have smaller effects on the genetic diversity of a species
254 than losing a diversity hotspot (e.g. glacial refugia, or source populations). This uncertainty can
255 be seen in the range of predicted genetic diversity change using study-specific z values (Fig. 4),
256 and the variability in the degree of fit of GDAR relationships, where in some species small areas
257 can contain high genetic diversity (Fig. S2). Estimating the dependence of genetic diversity on
258 area would be enhanced by species-specific knowledge of regions that are particularly
259 genetically diverse, or regions that are well-connected or sustain large populations. This issue
260 mirrors that widely recognized in the use of SARs, in that single z values are unable to capture
261 important spatial structure in geographic range sizes and the spatial turnover of species¹².

262 Second, range contractions can cause immediate loss of genetic diversity due to the loss of
263 individuals, however, the magnitude and spatial arrangement of area loss have long-term effects
264 that are not captured by GDARs. Patchy area loss and fragmentation can decrease gene flow

265 across species ranges. Smaller population sizes and reduced gene flow will, in turn, increase the
266 strength of genetic drift and introduce additional population structure. Increased drift will
267 accelerate the loss of genetic diversity for generations to come, and increases in population
268 structure will cause z to increase over time^{35–38}. While GDARs may eventually be able to predict
269 the immediate effects of reduced population size, they do not account for increasing rates of loss
270 over time³⁹.

271

272 **Conclusions**

273 Our understanding of GDARs is in its infancy, and further development could resolve some of
274 the issues we identify and improve our ability to use general rules to predict genetic diversity
275 loss. However, the relationship between population structure and the shape of GDARs means
276 that additional ecological and evolutionary information is likely necessary to estimate z values
277 for a given species or subset of species. Using a standard z value across species without
278 knowledge of spatial population structure will most often poorly estimate genetic diversity loss
279 for focal species. Predicted losses may not be comparable across different data types and genetic
280 diversity metrics. Further assessment and validation, including procedures for making informed
281 decisions about the value of scaling exponents in GDARs, may improve their usability. We
282 encourage more work to achieve a greater understanding of the factors that shape GDARs across
283 species before they are incorporated into the conservation genetic toolbox. Access to genetic
284 data, robust proxies of genetic diversity, and knowledge about population structure and diversity
285 hotspots within species remain essential for effectively protecting genetic diversity.

286

287 **Methods**

288 *Genetic diversity area relationships*

289 We used 55 publicly available microsatellite datasets that were previously compiled by Schmidt
290 et al. (for detailed methods on their compilation, see ^{17,40,41}). Briefly, we queried DataONE (a
291 platform to access multiple data repositories) and the Dryad Digital Repository between 2017 –
292 2021 using binomial species names and ‘microsat*’ as keywords. We retained data from wild
293 populations in their native range, and set a minimum sample size of 5 individuals per sample
294 location identified in the original publications. The datasets comprised 51 species with a median
295 579 individuals per dataset, ranging from 127 – 2232 individuals (Table S1). We set an *a priori*
296 cutoff of at least 10 sample locations per dataset for this study (median: 22 locations; range: 12-
297 100). We did not set thresholds for the minimum area sampled because we were primarily
298 interested in estimating z and F_{ST} from each dataset and testing relationships between them,
299 which does not require sample sites to be representative of the species as a whole. We quantified
300 population structure across the entire species sample using global F_{ST} . We estimated global F_{ST}
301 for each dataset in R⁴² with the `basic.stats()` function in the `hierfstat` package⁴³, which estimates
302 F_{ST} as $(H_t - H_s)/H_t$, where H_t = total heterozygosity and H_s = mean heterozygosity of
303 subpopulations.

304 To construct a GDAR for each dataset, we took a nested approach to artificially sample each
305 study area. We sampled a square area centered on each genetic sample location with half-side
306 lengths that were 10, 25, 50, 75, 90, and 99% of the study extent.

307 For each area sample, we recorded 1) the total number of alleles summed across loci; 2) rarefied
308 allelic richness (hereafter *allelic richness*; rarefied to the smallest sample size of a sample

309 location for a given dataset); and 3) gene diversity³² (evenness). These metrics differ in their
310 sensitivity to the presence of rare alleles and thus to the number of individuals sampled. Allele
311 count weights all alleles equally and is most strongly affected by sample size. It is also the most
312 representative of the extinction of a “mutation” or allele, which has been argued to be a key
313 focus of genetic conservation⁴⁴. Gene diversity is most affected by the frequencies of common
314 alleles, while rarefied allelic richness is intermediately affected by rare alleles. Allele count is
315 analogous to the number of single nucleotide polymorphisms, or allelic variants, used in⁸. We
316 estimated z of the power-law GDAR (genetic diversity = cA^z) for each genetic metric by taking
317 the slope estimated for the relationship between log area and log genetic diversity. For datasets
318 where this slope was not significant (linear regression, $p < 0.05$), we recorded slope (z) values as
319 NA. This resulted in the removal of 4 datasets for allelic richness (zAR), and 6 datasets for gene
320 diversity (zGD) for downstream analyses.

321 To quantify the dependence between the effects of area and population structure on genetic
322 diversity, we ran a multiple regression with log area, global F_{ST} , and their interaction as
323 predictors of each diversity metric (allele counts, allelic richness, and gene diversity) for a total
324 of 3 models. We included all datasets in a single model with study as a random intercept. Models
325 were fit in the lme4 package⁴⁵ in R. We then compared the effect sizes of area to models with
326 only area as a predictor.

327 We next assessed the extent to which average z values could predict the percentage of genetic
328 diversity lost for each of the 55 datasets individually—in other words, we tested whether use of a
329 single z value could be useful for predicting loss in a given species, which would represent its
330 use in applied conservation. To do this, we calculated genetic diversity change for each dataset
331 based on (1) the GDAR using z values estimated for that dataset, and (2) using the mean z values

332 for each genetic metric. We compared observed and predicted values of genetic diversity loss
333 using the mean z value and using the data-specific z value for the largest area loss (99%) for each
334 of the nested sample areas per dataset. Because the ratio of area loss was the same across all sites
335 and datasets, predicted genetic diversity loss differed only across datasets when study-specific z
336 values were used (Fig. 4). We then averaged the percent loss across area samples to obtain the
337 mean observed loss of genetic diversity for each dataset.

338

339 *Trait-based predictions of z*

340 We then explored the predictability of global F_{ST} and z values from readily accessible species-
341 level trait data. We tested 3 traits that are related to population structure: body mass (g),
342 individual home range area (km²), and geographic range size (km²). We restricted our analysis to
343 mammals because they had the most data, and we could make consistent predictions about the
344 relationships between traits and population structure. Generally, larger species tend to disperse
345 further, have larger individual home ranges, and larger geographic ranges^{46,47}. Additionally,
346 species with larger home ranges generally have less spatially structured populations, while
347 structure due to isolation by distance is likely higher in species with larger distributional ranges.

348 We compiled adult body mass data from the PanTHERIA database⁴⁸ via the R package
349 traitdata⁴⁹. We used home range sizes available from the HomeRange dataset^{50,51}, using
350 individual, adult home ranges estimated from wild animals. Finally, we obtained data on
351 geographic range sizes from species distribution maps available from the IUCN⁵². We filled in
352 missing data values from the literature where possible. For species with missing home range
353 data, we used the mean value of the genus if available. Because our focus was on model

354 predictive capacity, we disregarded collinearity among predictor variables. We also included the
355 sample extent of each dataset (i.e., the area of the bounding box covering all sample sites) as an
356 additional predictor. All three traits were available for 33 of the species in our data set. We
357 related these predictors to global F_{ST} and z values using multiple linear regressions. For models
358 with global F_{ST} as a response variable, which varies between 0 and 1, we fit beta regressions with
359 a logit link function in the `betareg` package⁵³. We used normally distributed errors for models
360 with z values as response variables because z is not by definition bound by 0 and 1.

361 We then tested model predictive accuracy by partitioning our dataset into training and test
362 datasets (80 and 20% of the data, respectively). We created 1000 partitions and recorded the
363 coefficient of variation (root mean squared error divided by the mean observed z or F_{ST}) to
364 measure the relative error rates of each model.

365 As an additional test, we assessed whether our model maintained similar predictive capacity for
366 mammal F_{ST} values derived from an independent dataset, the MacroPopGen database^{33,34}.
367 MacroPopGen reports pairwise or global F_{ST} values for terrestrial vertebrates and freshwater fish
368 across the Americas compiled from literature reports, and is based on studies that used
369 microsatellite data. After filtering for mammal species, we applied additional filters for sample
370 locations with more than 5 individuals and species with 10 or more sample locations for
371 consistency with our compiled dataset. We note F_{ST} estimates from data with fewer individuals
372 sampled or more local sampling are less likely to be associated with species-level traits. When
373 global F_{ST} was not reported, we calculated mean pairwise F_{ST} values for populations within a
374 study, which is correlated with global F_{ST} . In total, 53 F_{ST} estimates from MacroPopGen and trait
375 data were available for 36 species (Table S5). We assessed predictability using the same
376 approach described above.

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385

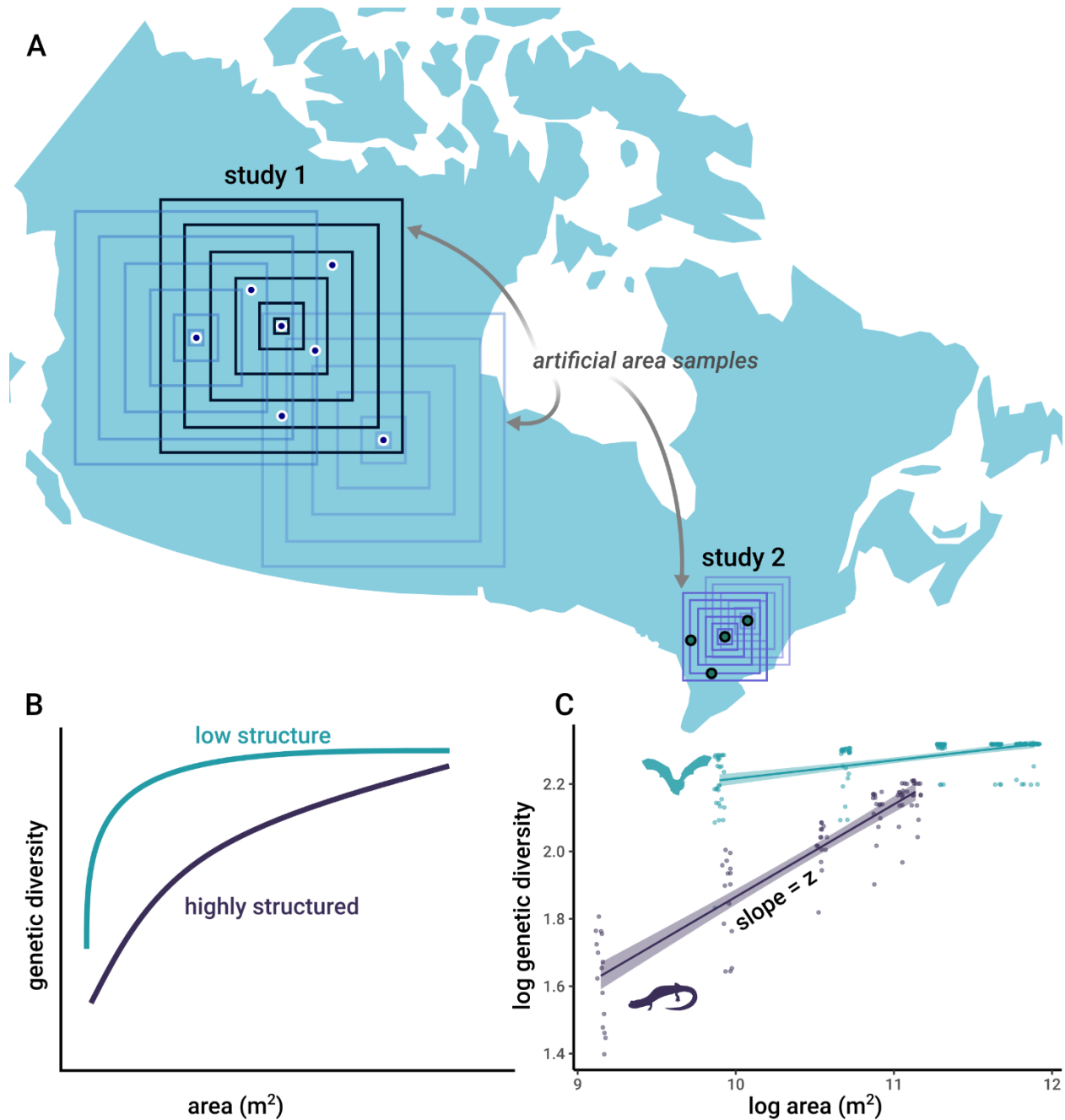
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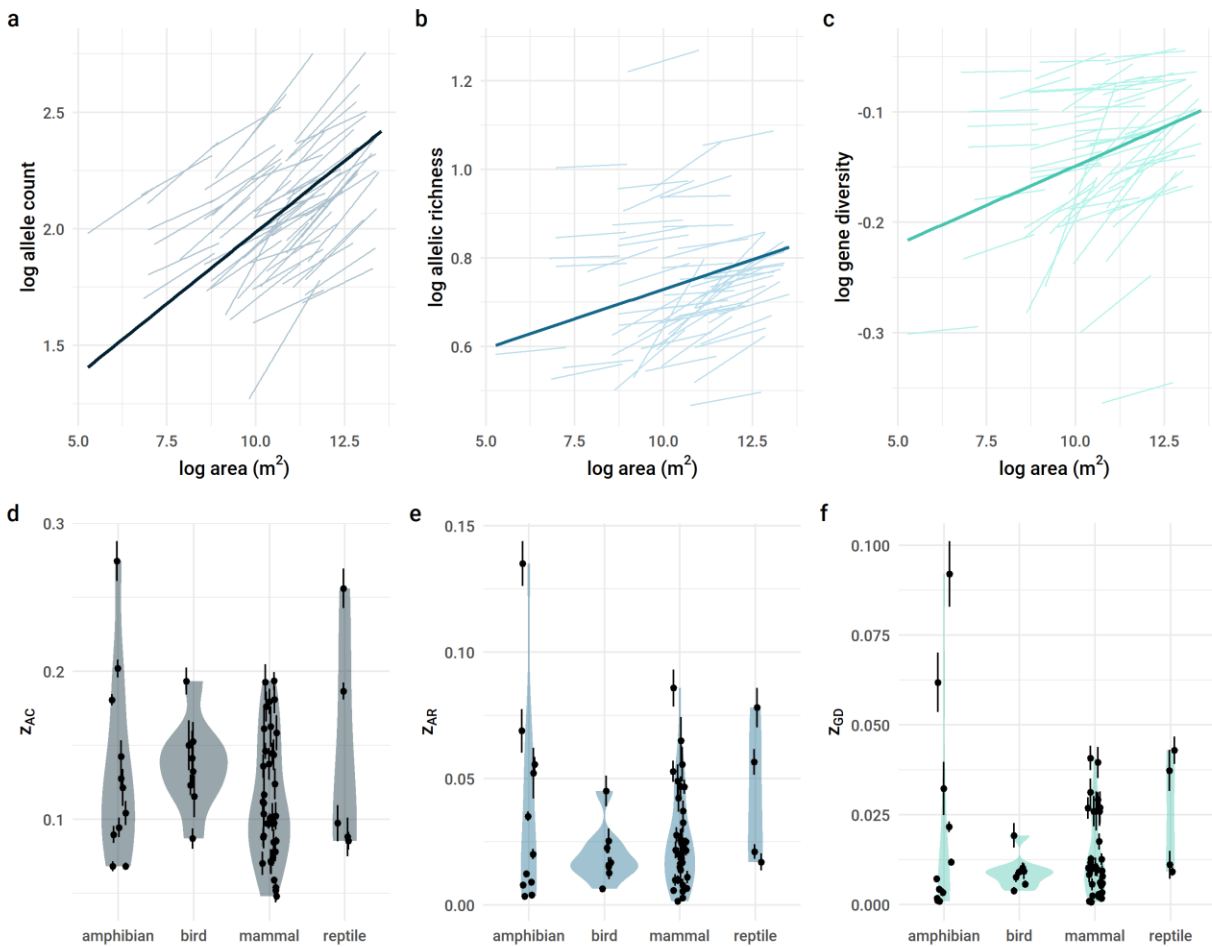
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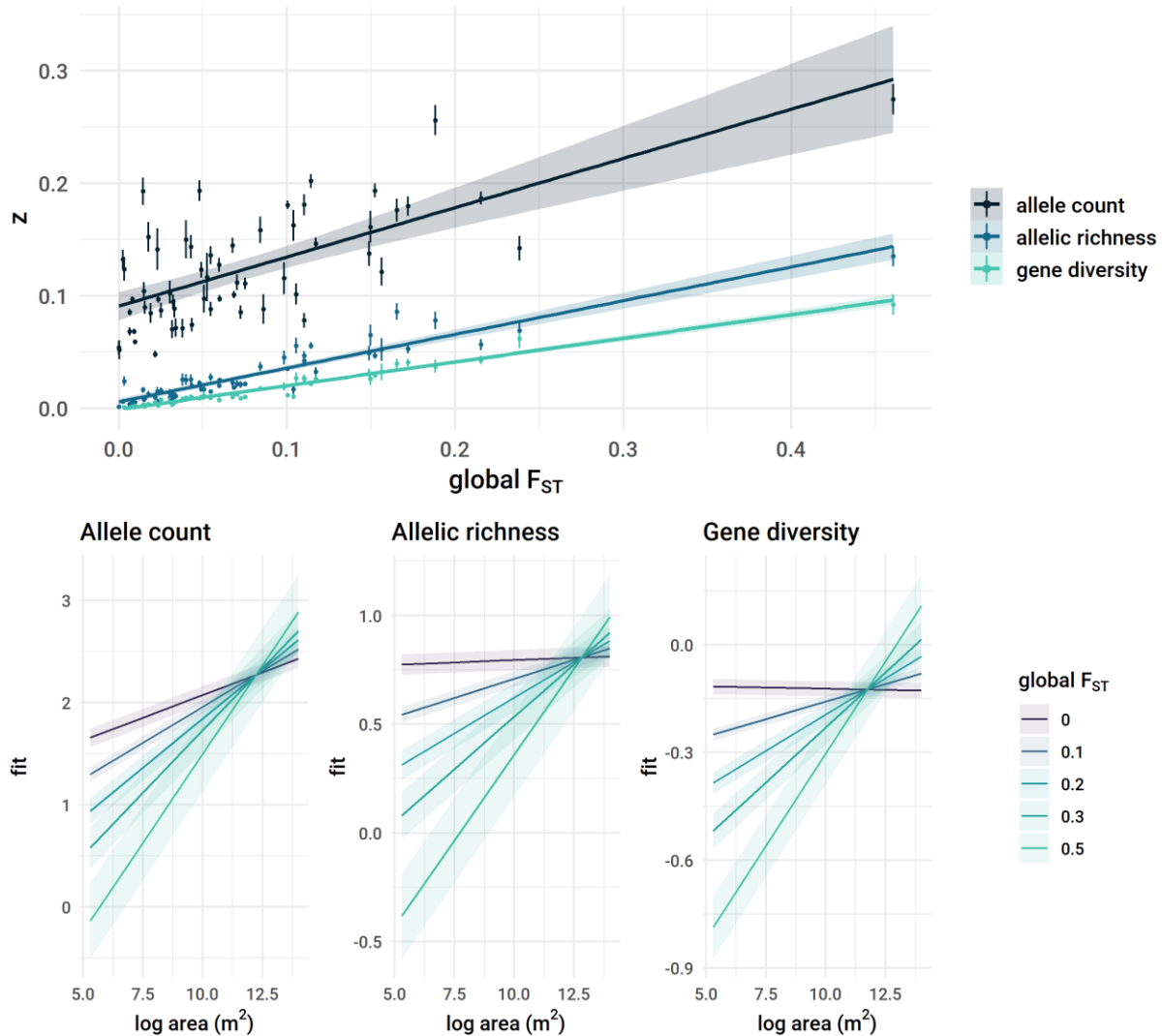


501
 502 **Figure 1.** GDAR sampling design and predictions for two hypothetical studies. **A)** For each
 503 sample location within a study, we assessed genetic diversity as aggregates of all samples
 504 contained within each of 6 concentric quadrats of increasing size. **B)** We then constructed a
 505 study's GDAR as the average relationship with area across all its samples assessed in this way,
 506 with an estimated scaling exponent, z , describing the relationship between area and genetic
 507 diversity in log-log space. In species with little genetic structuring (low F_{ST}), alleles are more
 508 evenly spread over the landscape and even small areas can harbor large proportions of the alleles
 509 present in the entire study sample. Thus, we expect GDARs will more rapidly level off (shallow
 510 slope, smaller z) compared to species that are highly genetically structured (high F_{ST} , steep slope,
 511 high z). **C)** These predictions are demonstrated in two species with contrasting movement

512 abilities, the little brown bat (*Myotis lucifugus*) and the Mount Lyell salamander (*Hydromantes*
513 *platycephalus*). In this example, genetic diversity is measured using allele count. Shaded regions
514 are 95% confidence intervals of the fitted line. Due to its flight ability, we predict that the little
515 brown bat should exhibit less population structure than a comparatively less vagile salamander
516 species due to higher possibility of gene flow.



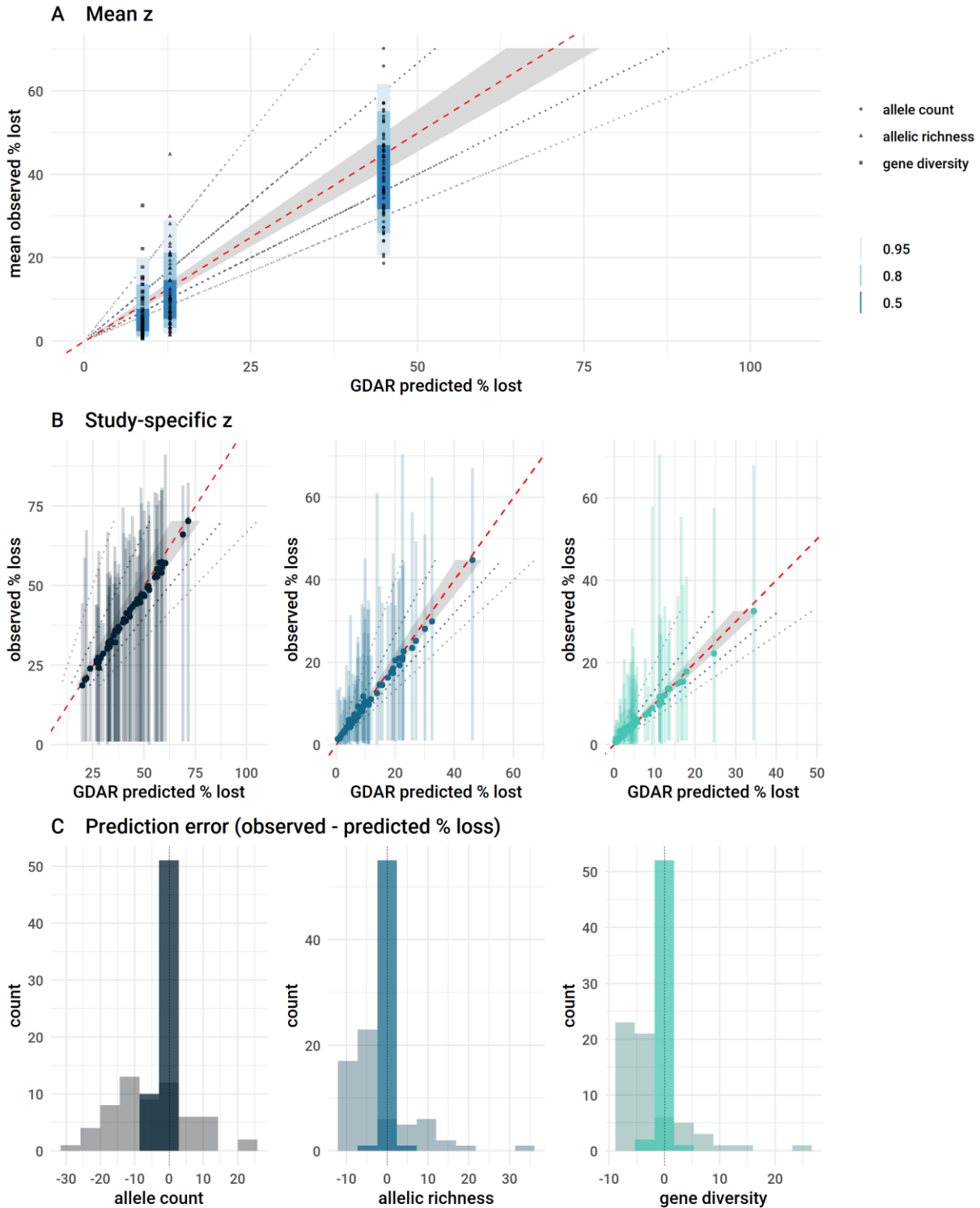
519 **Figure 2.** (A-C) Genetic diversity—area relationships in terrestrial vertebrates assessed across
 520 three genetic metrics. Lighter lines are log diversity vs. log area for each dataset. Dark lines
 521 depict the overall relationship across all datasets. The slope of each line is the scaling exponent z .
 522 (D-F) Plots of z values for each genetic metric (z_{AC} = allele count, z_{AR} = allelic richness, z_{GD} =
 523 gene diversity) by vertebrate class. Points represent estimated z values and lines denote the
 524 standard error.



525

526

527 **Figure 3.** The effect of area on genetic diversity depends on population differentiation (measured
 528 with global F_{ST}). **(Top)** The top plot shows the strong correlation between study-specific z values
 529 and F_{ST} for all metrics of genetic diversity. Each point represents a single genetic dataset (some
 530 species are represented by multiple datasets), and lines denote the standard error of z estimates.
 531 **(Bottom)** Models fitted to the 51 species that included the main effects and interaction of log
 532 area and F_{ST} as predictors of genetic diversity. Ribbons denote 95% confidence intervals around
 533 the mean effect (solid line). For all diversity metrics, the effect of area strengthens as F_{ST}
 534 increases. Gene diversity and allelic richness are unrelated to area when there is no population
 535 structure ($F_{ST} = 0$). The three metrics are shown in order of decreasing sensitivity to sample size:
 536 allele counts, rarefied allelic richness, and gene diversity.



537

538 **Figure 4.** Observed versus predicted change in genetic diversity. (A-B) Each point represents the
 539 average percent decrease of alleles, allelic richness, or gene diversity after removing 99% of area
 540 for each dataset. Red dashed lines depict 100% correlation, grey bands show 10% intervals
 541 above or below observed loss, dark and light grey dotted lines show 25% and 50% intervals

542 around observed loss. **(A)** Predicted vs. observed genetic diversity change from GDARs using
543 the mean z value across all studies for each genetic metric (see Table S2). Colored slabs show the
544 distribution of data within 95%, 80%, and 50% quantiles. **(B)** Predicted genetic diversity change
545 from GDAR using study-specific z values. Lines flanking points show the range of observed
546 percent genetic diversity loss for each study. **(C)** Histograms show the spread of prediction
547 residuals (the difference between mean observed diversity loss and predicted diversity loss) for
548 each diversity metric. Prediction errors using study level z values are shown by more opaque
549 bars, and more transparent bars show the distribution of prediction error using average z values.
550 Dashed vertical lines indicate 0 prediction error.

551

Supplementary information for: Variability, drivers, and utility of genetic diversity-area relationships in terrestrial vertebrates

Chloé Schmidt, Sean Hoban, Deborah M. Leigh, Walter Jetz, Colin J. Garroway

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Figures S1 – S4

Table S1. Data summary. The number of sites, total individuals across all sites, estimated global F_{ST} , estimated z values for each genetic metric, and references are given for each dataset (rows). NA values for z indicate that the effect of area on genetic diversity was not significant and corresponding datasets were thus omitted from further analyses of z .

class	species	sites	individuals	global F_{ST}	z_{AC}	z_{AR}	z_{GD}	references
amphibian	<i>Ambystoma maculatum</i>	56	1292	0.0092	0.07	0.00	0.00	1,2
amphibian	<i>Lithobates sylvaticus</i>	39	888	0.0064	0.07	0.00	0.00	1,2
amphibian	<i>Lithobates sylvaticus</i>	29	766	0.0598	0.13	0.02	0.01	3,4
amphibian	<i>Ambystoma maculatum</i>	19	489	0.1564	0.12	0.05	0.03	5,6
amphibian	<i>Ascaphus montanus</i>	100	1968	0.1143	0.20	0.06	0.02	7,8
amphibian	<i>Ambystoma barbouri</i>	76	1601	0.1005	0.18	0.03	0.01	9,10
amphibian	<i>Plethodon albagula</i>	21	343	0.0149	0.10	0.01	0.00	11,12
amphibian	<i>Ambystoma maculatum</i>	22	626	0.0324	0.09	0.01	0.00	13,14
amphibian	<i>Lithobates sylvaticus</i>	22	469	0.0156	0.09	0.01	0.00	13,14
amphibian	<i>Rana draytonii</i>	17	298	0.2384	0.14	0.07	0.06	15,16
amphibian	<i>Hydromantes platycephalus</i>	15	195	0.4605	0.27	0.14	0.09	17,18
bird	<i>Poecile atricapillus</i>	32	911	0.0480	0.19	0.02	0.01	19,20
bird	<i>Campylorhynchus brunneicapillus</i>	12	363	0.0984	0.12	0.05	0.02	21,22
bird	<i>Geospiza fortis</i>	11	202	0.0401	0.15	0.03	0.01	23,24
bird	<i>Geospiza fuliginosa</i>	11	198	0.0229	0.14	0.02	0.01	23,24
bird	<i>Geospiza fuliginosa</i>	21	517	0.0025	0.13	0.01	NA	25,26
bird	<i>Aphelocoma californica</i>	30	463	0.0492	0.12	0.02	0.01	27,28
bird	<i>Poecile hudsonicus</i>	13	260	0.0176	0.15	0.01	0.00	29,30
bird	<i>Strix occidentalis</i>	17	423	0.0251	0.09	0.02	0.01	31
mammal	<i>Sus scrofa</i>	18	551	0.1040	0.16	0.02	0.01	32,33
mammal	<i>Capreolus capreolus</i>	13	371	0.1489	0.14	0.05	0.03	34,35
mammal	<i>Pekania pennanti</i>	34	722	0.0685	0.10	0.02	0.01	36,37
mammal	<i>Nyctalus leisleri</i>	14	183	0.0190	0.08	NA	NA	38,39
mammal	<i>Myotis lucifugus</i>	15	735	0.0005	0.05	NA	NA	40,41
mammal	<i>Vicugna vicugna</i>	14	374	0.1498	0.16	0.06	0.03	42,43
mammal	<i>Tamiasciurus douglasii</i>	14	186	0.0305	0.10	0.01	0.01	44,45
mammal	<i>Tamiasciurus hudsonicus</i>	12	188	0.0525	0.12	NA	NA	44,45

mammal	<i>Lepus americanus</i>	39	853	0.1524	0.19	0.05	0.03	46,47
mammal	<i>Ursus arctos</i>	16	831	0.1055	0.10	0.06	0.03	48,49
mammal	<i>Ursus maritimus</i>	11	318	0.0435	0.07	0.02	0.01	48,49
mammal	<i>Myotis lucifugus</i>	21	1054	0.0145	0.19	0.02	0.00	50,51
mammal	<i>Ovis canadensis</i>	14	579	0.1102	0.08	0.04	0.03	52,53
mammal	<i>Meles meles</i>	30	675	0.1721	0.18	0.05	0.04	54,55
mammal	<i>Microtus arvalis</i>	53	855	0.0064	0.09	0.00	0.00	56,57
mammal	<i>Canis latrans</i>	41	303	0.0236	0.10	0.01	0.00	58,59
mammal	<i>Rousettus aegyptiacus</i>	34	490	0.0705	0.11	0.02	0.01	60,61
mammal	<i>Myotis lucifugus</i>	29	1310	0.0000	0.05	0.00	NA	62,63
mammal	<i>Myotis septentrionalis</i>	15	896	0.0032	0.12	0.02	0.00	62,63
mammal	<i>Martes americana</i>	29	653	0.0217	0.05	0.01	0.01	64,65
mammal	<i>Lemmus lemmus</i>	13	276	0.0304	0.10	0.01	0.01	66,67
mammal	<i>Odocoileus hemionus</i>	60	1714	0.1173	0.15	0.03	0.03	68,69
mammal	<i>Rangifer tarandus</i>	18	634	0.0319	0.07	0.01	0.00	70,71
mammal	<i>Lynx canadensis</i>	28	702	0.0097	0.06	0.01	0.00	72,73
mammal	<i>Felis silvestris</i>	15	620	0.0841	0.16	0.04	0.02	74,75
mammal	<i>Alces alces</i>	16	694	0.0429	0.14	0.03	0.01	76,77
mammal	<i>Ursus maritimus</i>	14	2232	0.0332	0.09	0.01	0.01	78,79
mammal	<i>Ursus americanus</i>	28	504	0.1104	0.18	0.05	0.03	80,81
mammal	<i>Myotis escaleraei</i>	15	442	0.0378	0.07	0.03	0.01	82,83
mammal	<i>Lynx rufus</i>	52	1646	0.0600	0.10	0.03	0.01	84,85
mammal	<i>Odocoileus virginianus</i>	64	2069	0.0081	0.10	0.01	0.00	86,87
mammal	<i>Rangifer tarandus</i>	27	508	0.0752	0.11	0.02	0.01	88,89
mammal	<i>Rhinolophus ferrumequinum</i>	27	950	0.0339	0.07	0.01	0.01	90,91
mammal	<i>Rangifer tarandus</i>	27	802	0.0676	0.14	0.02	0.01	92,93
mammal	<i>Miniopterus schreibersii</i>	22	312	0.0548	0.09	0.01	0.01	94,95
mammal	<i>Sorex antinorii</i>	17	213	0.0546	0.14	0.03	0.01	96,97
mammal	<i>Cervus elaphus</i>	27	638	0.1654	0.18	0.09	0.04	98,99
reptile	<i>Gopherus polyphemus</i>	46	933	0.2153	0.19	0.06	0.04	100,101
reptile	<i>Amblyrhynchus cristatus</i>	13	467	0.0860	0.09	NA	NA	102,103
reptile	<i>Liolaemus tenius</i>	15	127	0.1883	0.26	0.08	0.04	104,105

reptile	<i>Dipsosaurus dorsalis</i>	19	308	0.0725	0.09	0.02	0.01	106,107
reptile	<i>Uma inornata</i>	13	268	0.0507	0.10	0.02	0.01	108,109

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Table S2. GDAR scaling exponents (z-values) for terrestrial vertebrates summarized across taxonomic groups (overall values) and for each taxonomic class. Means and standard deviations of z-values are given for allele counts (z_{AC}), allelic richness (z_{AR}), and gene diversity GDARs (z_{GD}).

	z_{AC}	z_{AR}	z_{GD}
overall	0.12 ± 0.05	0.03 ± 0.02	0.02 ± 0.02
amphibian	0.13 ± 0.06	0.04 ± 0.04	0.02 ± 0.03
bird	0.14 ± 0.03	0.02 ± 0.01	0.01 ± 0.00
mammal	0.11 ± 0.04	0.03 ± 0.02	0.01 ± 0.01
reptile	0.14 ± 0.08	0.04 ± 0.03	0.03 ± 0.02

Table S3. Comparison of area effect sizes between models with area alone, and global F_{ST} and an area* F_{ST} interaction as predictors. Effect sizes and standard errors are given for area, F_{ST} , and the interaction between area and F_{ST} where applicable. All effects were significant ($p < 0.05$) in all models. The area effect is strongly reduced when F_{ST} and their interaction are included in the model. For gene diversity and allelic richness, when populations are panmictic ($F_{ST} = 0$), the effect of area is negligible (bold values). The coefficient for the interaction terms are orders of magnitude larger than the area effect, demonstrating that the effect of area is strongly mediated by population structure (see also Figure S2 for plotted interaction effects). We show the effect size of F_{ST} only for complete understanding of the magnitude of the interactive effect with area. We caution against causal interpretations of F_{ST} on genetic diversity because genetic diversity (alpha diversity) and genetic differentiation (beta diversity) reflect two measures of diversity that influence each other and are products of the same processes.

genetic metric	model	area	F_{ST}	area* F_{ST} interaction
gene diversity	area	0.01 ± 0.0003	--	--
	interaction	-0.001 ± 0.0004	-2.44 ± 0.11	0.21 ± 0.004
allelic richness	area	0.02 ± 0.0005	--	--
	interaction	0.004 ± 0.0007	-3.95 ± 0.24	0.31 ± 0.007
allele count	area	0.13 ± 0.001	--	--
	interaction	0.09 ± 0.001	-6.33 ± 0.46	0.50 ± 0.01

Table S4. Model summaries for relationships between F_{ST} , z values derived from allele count (zAC), allelic richness (zAR), and gene diversity (zGD), and predictor variables including: home range size (km²), species range size (km²), species body mass (g), and the area of the spatial extent of the sample locations in each dataset (km²). All predictors were log-transformed prior to analysis. Because F_{ST} is bounded by 0 and 1, we used a beta regression and report pseudo- R^2 to summarize explained variation. Z values are not bounded by 0 and 1 thus we used linear regressions with normally distributed errors and report adjusted R^2 (R^2_{adj}), which corrects for the number of predictors included in the model, to summarize explained variation. Estimated slopes for each predictor are given with 95% confidence intervals. Relationships were typically stronger in the F_{ST} model compared to z models, where predictor effects tended to be small.

	predictor	estimate	95% CI
F_{ST} pseudo $R^2 = 0.52$	home range	-0.19	-0.34 – -0.04
	range size	-0.44	-0.89 – 0.01
	body mass	0.30	0.14 – 0.45
	sampled area size	0.20	0.10 – 0.30
zAC $R^2_{adj} = 0.39$	home range	-0.02	-0.03 – -0.01
	range size	0.01	-0.02 – 0.04
	body mass	0.01	-0.00 – 0.02
	sampled area size	0.01	0.00 – 0.02
zAR $R^2_{adj} = 0.38$	home range	0.00	-0.01 – -0.00
	range size	-0.01	-0.03 – -0.00
	body mass	0.01	0.00 – 0.01
	sampled area size	0.00	0.00 – 0.01
zGD $R^2_{adj} = 0.42$	home range	0.00	-0.01 – -0.00
	range size	-0.01	-0.01 – 0.00
	body mass	0.00	0.00 – 0.01
	sampled area size	0.00	0.00 – 0.00

Table S5. F_{ST} estimates from the MacroPopGen database and associated trait data.

species	F_{ST}	mass (g)	species range size (km²)	home range size (km²)	sample area (km²)
<i>Alces alces</i>	0.14	461900.76	23096275.49	40.49	175366.25
<i>Alces alces</i>	0.10	461900.76	23096275.49	40.49	1771220.04
<i>Bison bison</i>	0.12	624577.07	140673.07	605.92	2570587.13
<i>Chrysocyon brachyurus</i>	0.13	23325.00	4335910.28	54.07	3007362.49
<i>Ctenomys minutus</i>	0.20	92.00	54952.67	0.00	1164.51
<i>Cynomys ludovicianus</i>	0.12	797.05	1820824.74	0.00	319.71
<i>Cynomys parvidens</i>	0.29	899.98	31805.77	0.00	13315.57
<i>Didelphis virginiana</i>	0.07	2442.08	6033226.94	0.44	1098.05
<i>Gulo gulo</i>	0.07	12792.49	24394376.49	553.13	10655064.79
<i>Lepus americanus</i>	0.18	1568.42	9597267.58	0.08	19945447.02
<i>Lontra canadensis</i>	0.07	8087.42	19086449.84	0.17	191718.98
<i>Lycalopex vetulus</i>	0.03	4233.47	1782063.08	3.85	2323208.40
<i>Lynx rufus</i>	0.07	6374.47	9879514.31	19.88	9189982.82
<i>Lynx rufus</i>	0.10	6374.47	9879514.31	19.88	10394522.78
<i>Lynx rufus</i>	0.02	6374.47	9879514.31	19.88	168693.39
<i>Marmota flaviventris</i>	0.13	3709.73	1718256.72	0.04	159109.65
<i>Martes americana</i>	0.06	873.69	7637869.53	4.36	11660211.07
<i>Martes americana</i>	0.25	873.69	7637869.53	4.36	6760157.05
<i>Pekania pennanti</i>	0.14	3750.00	3711380.88	26.97	5743415.25
<i>Microtus californicus</i>	0.22	57.42	287643.37	0.00	76221.24
<i>Ochotona princeps</i>	0.22	157.63	894661.41	0.00	1434.21
<i>Odocoileus virginianus</i>	0.01	75901.25	14410636.17	1.39	1048733.76
<i>Ondatra zibethicus</i>	0.18	991.31	14688578.52	0.01	11328640.61
<i>Oreamnos americanus</i>	0.19	72105.40	801852.34	39.50	4725770.76
<i>Ovis canadensis</i>	0.16	74644.87	532974.92	19.56	63031.27
<i>Ovis canadensis</i>	0.26	74644.87	532974.92	19.56	1837485.48
<i>Ovis dalli</i>	0.16	70194.13	816225.07	7.84	2537227.55
<i>Panthera onca</i>	0.11	83943.09	9026158.26	161.37	26153976.40
<i>Panthera onca</i>	0.10	83943.09	9026158.26	161.37	26001315.13
<i>Panthera onca</i>	0.04	83943.09	9026158.26	161.37	367694.81
<i>Peromyscus leucopus</i>	0.04	18.07	5831351.77	0.00	64.76
<i>Peromyscus leucopus</i>	0.02	18.07	5831351.77	0.00	69760.20
<i>Peromyscus maniculatus</i>	0.16	19.98	13030881.66	0.00	71652.19
<i>Puma concolor</i>	0.03	53954.05	21145707.25	219.93	1502430.99
<i>Puma concolor</i>	0.09	53954.05	21145707.25	219.93	802285.37
<i>Puma concolor</i>	0.09	53954.05	21145707.25	219.93	49202.25
<i>Puma concolor</i>	0.09	53954.05	21145707.25	219.93	920939.26
<i>Rangifer tarandus</i>	0.35	109088.50	18660769.81	426.50	514089.62
<i>Rangifer tarandus</i>	0.04	109088.50	18660769.81	426.50	2002962.38
<i>Rangifer tarandus</i>	0.09	109088.50	18660769.81	426.50	1494784.44
<i>Rangifer tarandus</i>	0.13	109088.50	18660769.81	426.50	15220188.89

<i>Rattus norvegicus</i>	0.07	282.89	18826152.77	0.02	63.83
<i>Tamias ruficaudus</i>	0.08	60.06	147850.63	0.00	72050.94
<i>Tamias striatus</i>	0.05	90.50	4197616.69	0.00	24743.56
<i>Urocitellus brunneus</i>	0.26	300.00	1286.80	0.01	31682.52
<i>Ursus americanus</i>	0.23	110500.00	10469239.77	131.07	481369.34
<i>Ursus americanus</i>	0.11	110500.00	10469239.77	131.07	62483.39
<i>Ursus arctos</i>	0.15	196287.50	24216958.81	337.72	3104094.30
<i>Ursus arctos</i>	0.05	196287.50	24216958.81	337.72	706656.94
<i>Ursus maritimus</i>	0.03	371703.81	22605603.23	78541.43	9409086.03
<i>Vicugna vicugna</i>	0.14	47499.61	618703.14	0.03	469293.97
<i>Vulpes velox</i>	0.08	2088.00	599398.12	11.80	956737.27

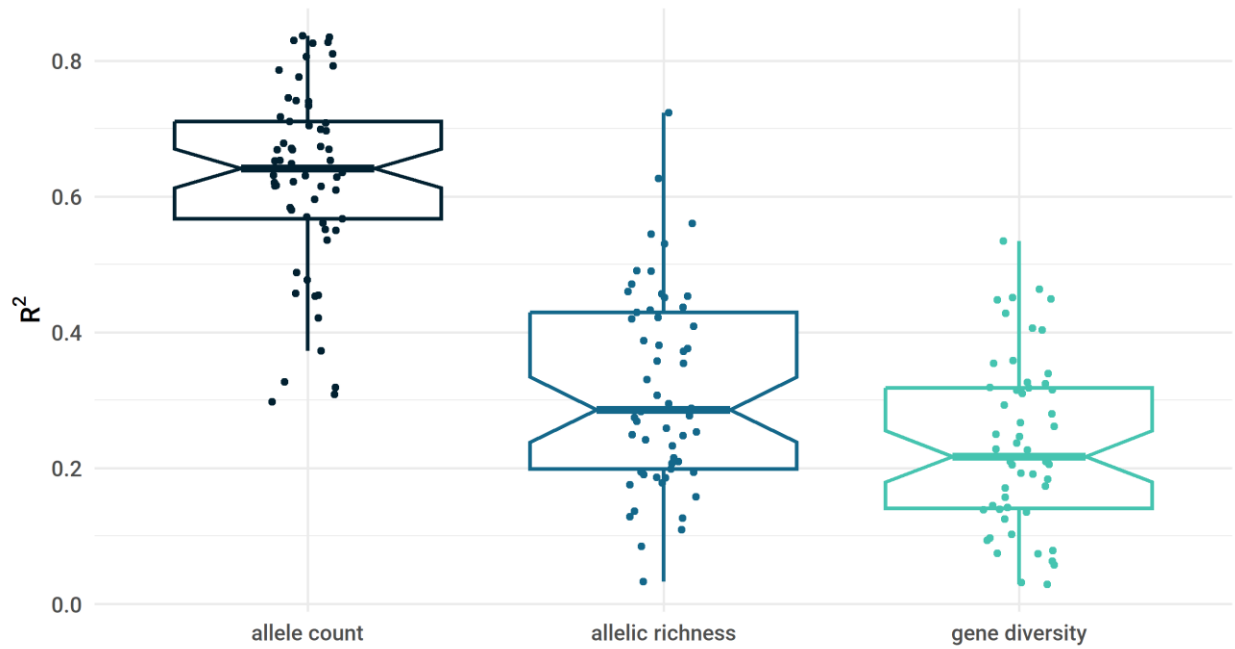
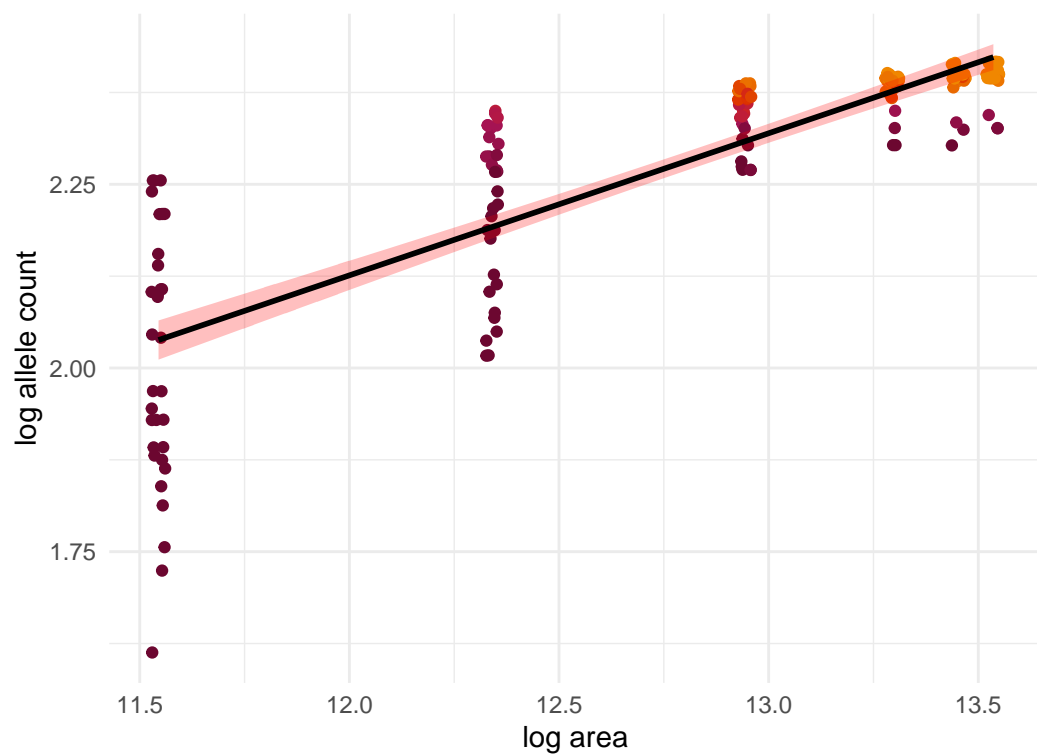


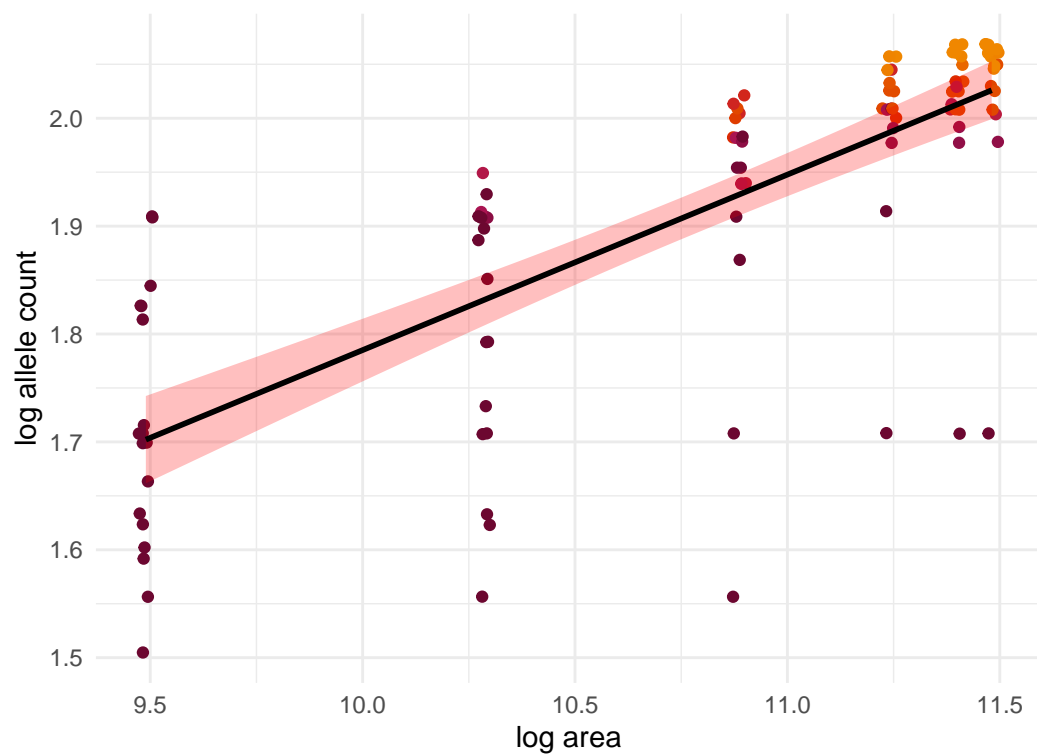
Figure S1. Box plots of variance in genetic diversity explained by area (R^2) for each genetic metric. Points are the R^2 of a simple linear model of the log-log relationship between each genetic metric (x axis) and area for each dataset. As expected, the variance in diversity explained by area is higher in genetic diversity metrics that are more strongly affected by sample size. This general pattern was consistent across all taxonomic groups.

Figure S2. Genetic diversity vs area plotted on a log-log scale for all 61 datasets. Red-shaded regions are 95% confidence intervals for the effect of area on genetic diversity. The slopes of these relationships are the scaling exponents z (values are reported in each plot title; they are NA when the relationship was not significant). Plots for allele count, allelic richness, and gene diversity are shown consecutively: note the genetic metric on the y axis. Point color denotes sample size, with lighter colors indicating greater numbers of individuals sampled.

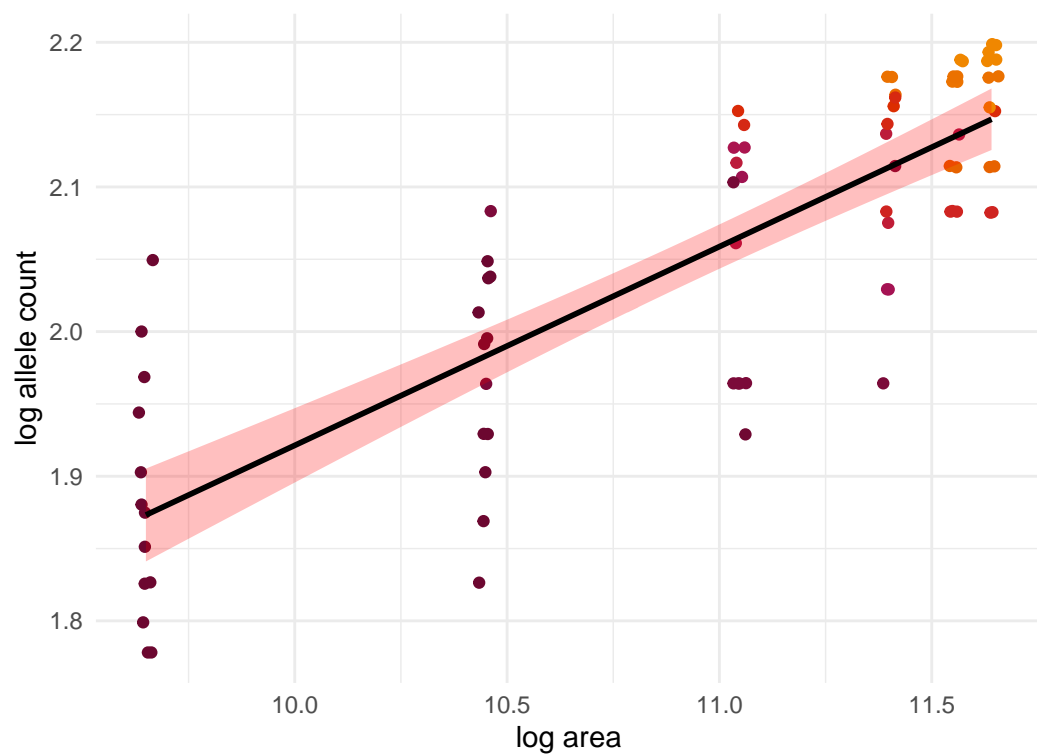
Poecile atricapillus; $z=0.193$



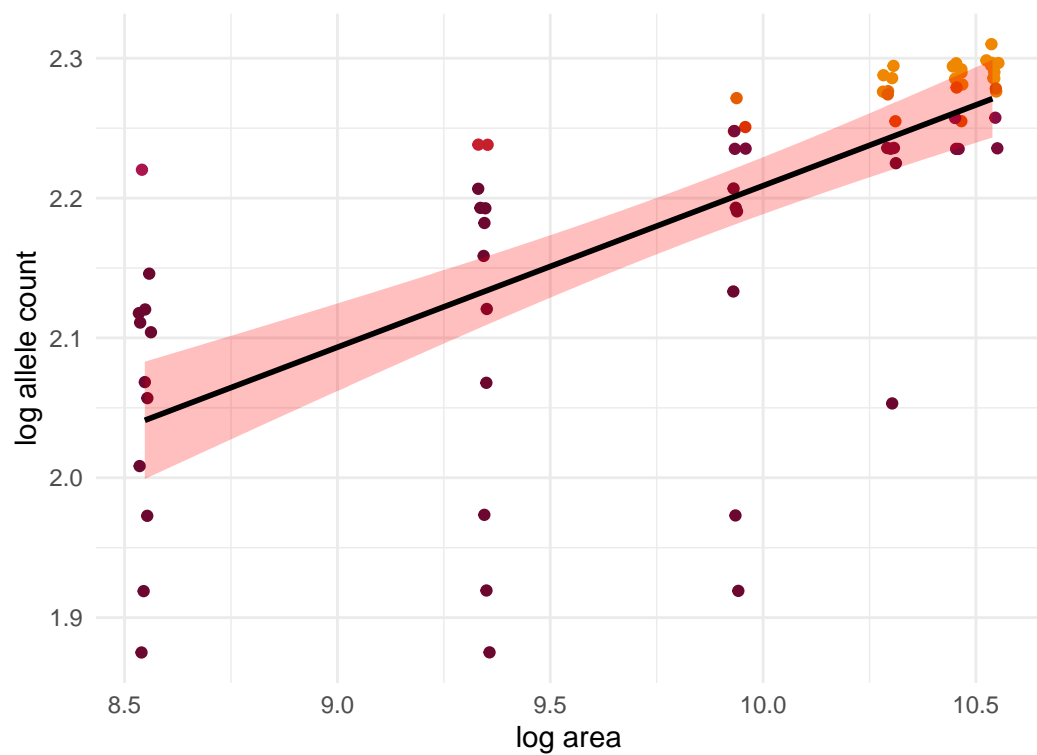
Sus scrofa; $z=0.163$



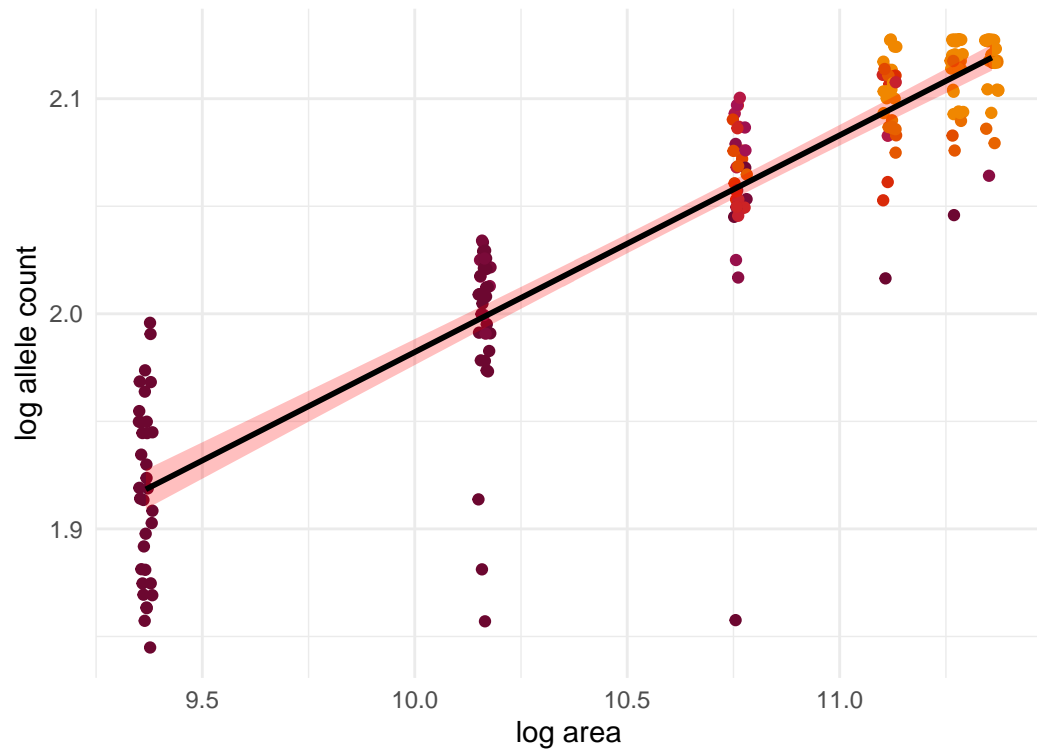
Capreolus capreolus; $z=0.137$



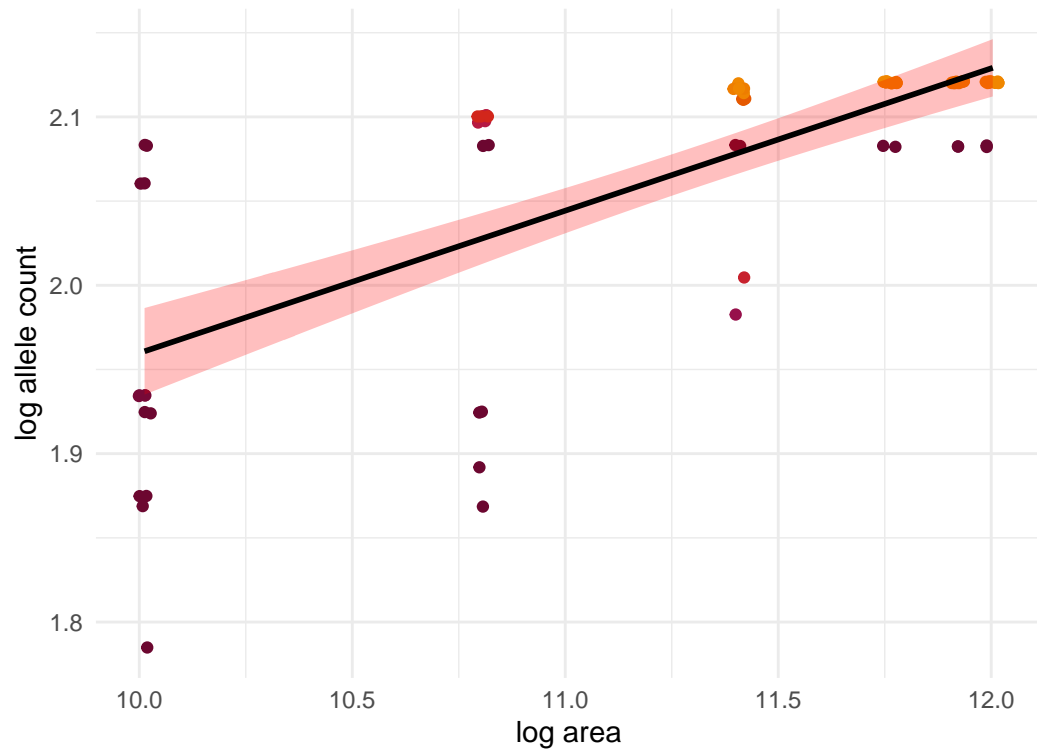
Campylorhynchus brunneicapillus; $z=0.116$



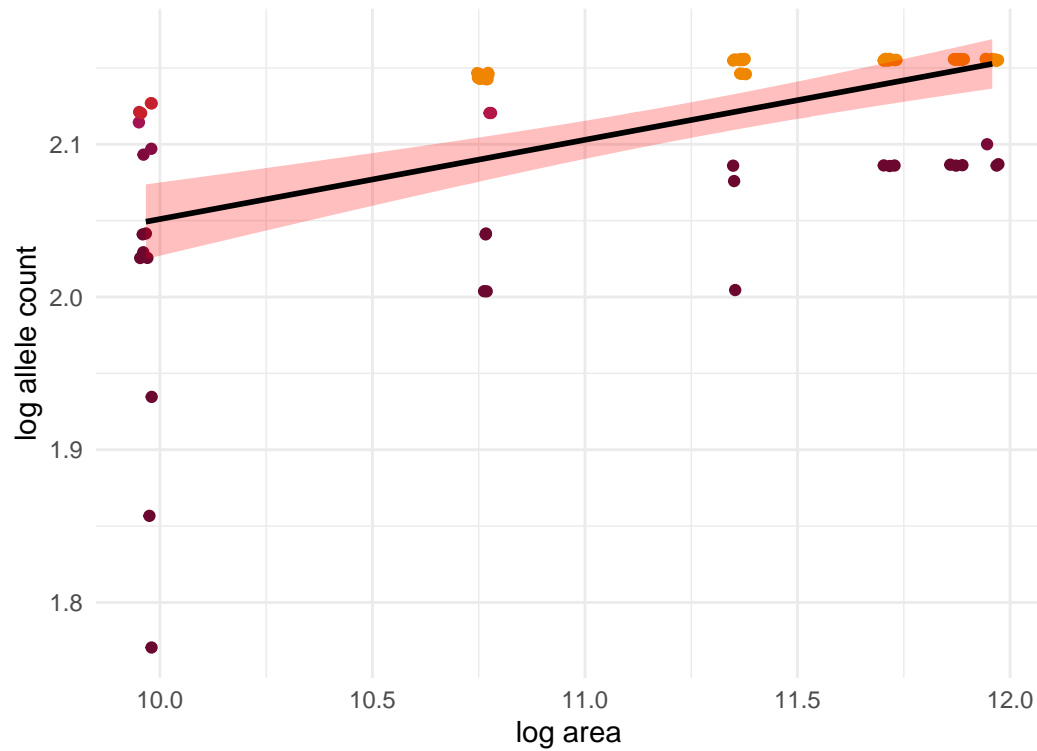
Pekania pennanti; $z=0.101$



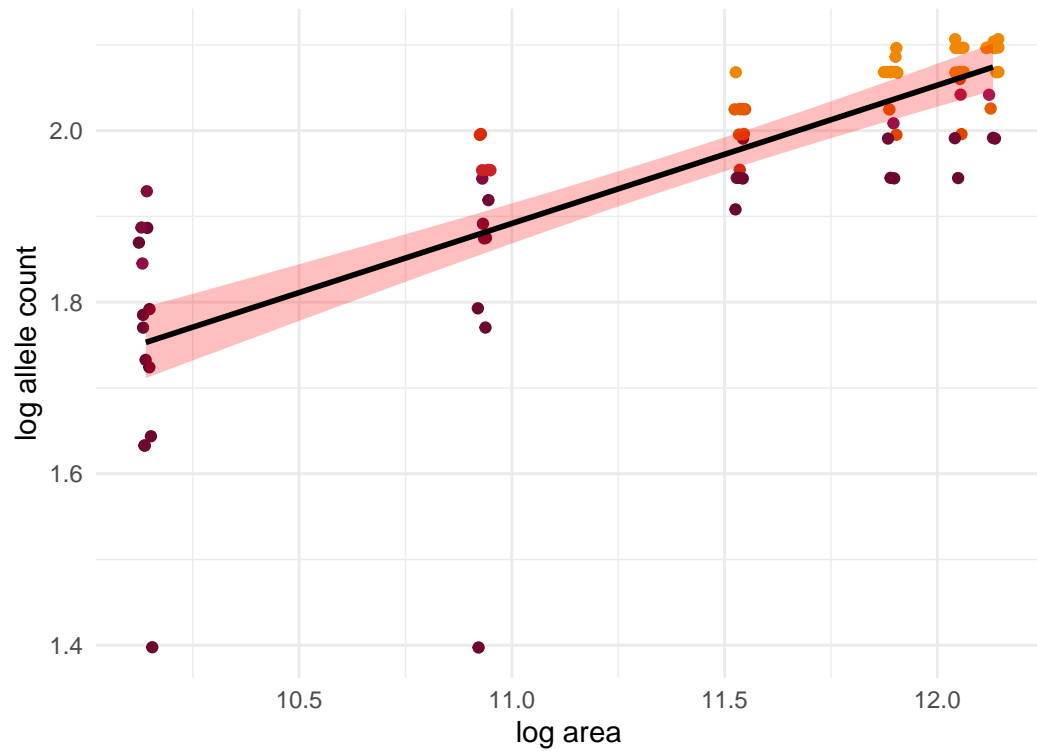
Nyctalus leisleri; $z=0.085$



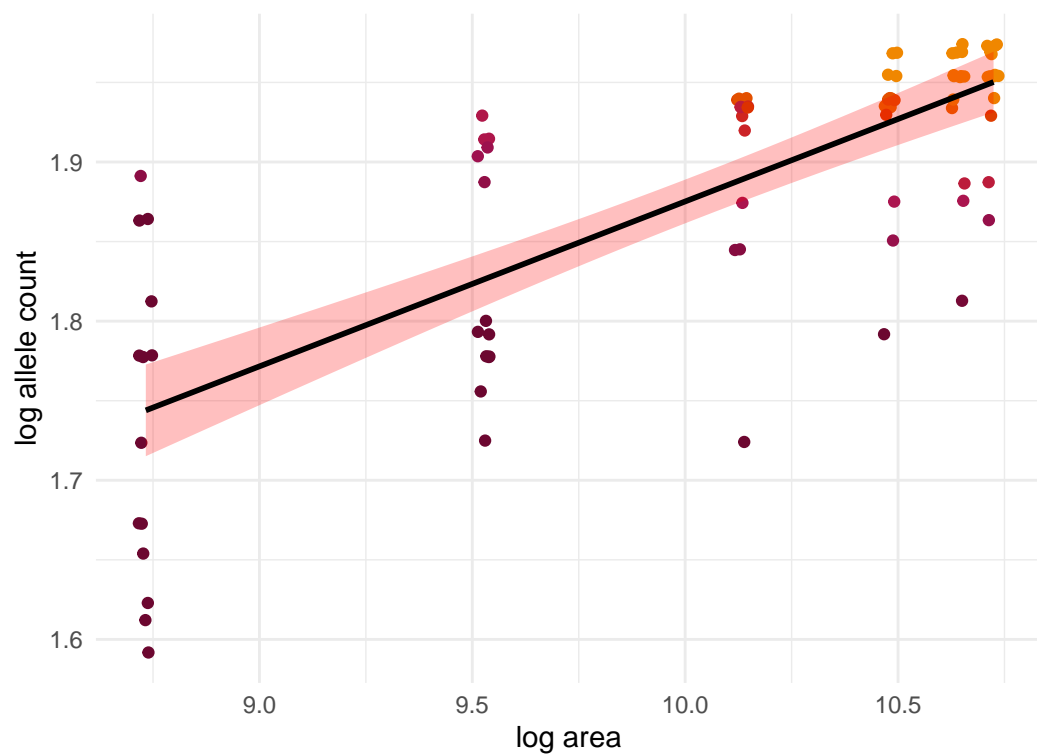
Myotis lucifugus; $z=0.052$



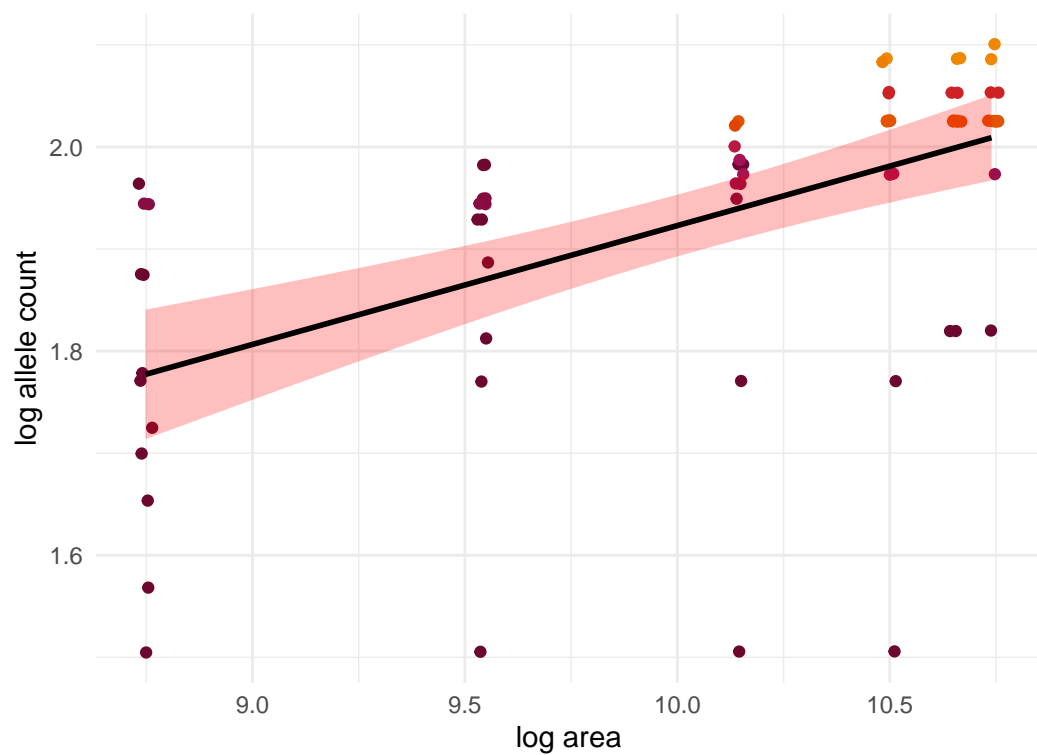
Vicugna vicugna; $z=0.161$



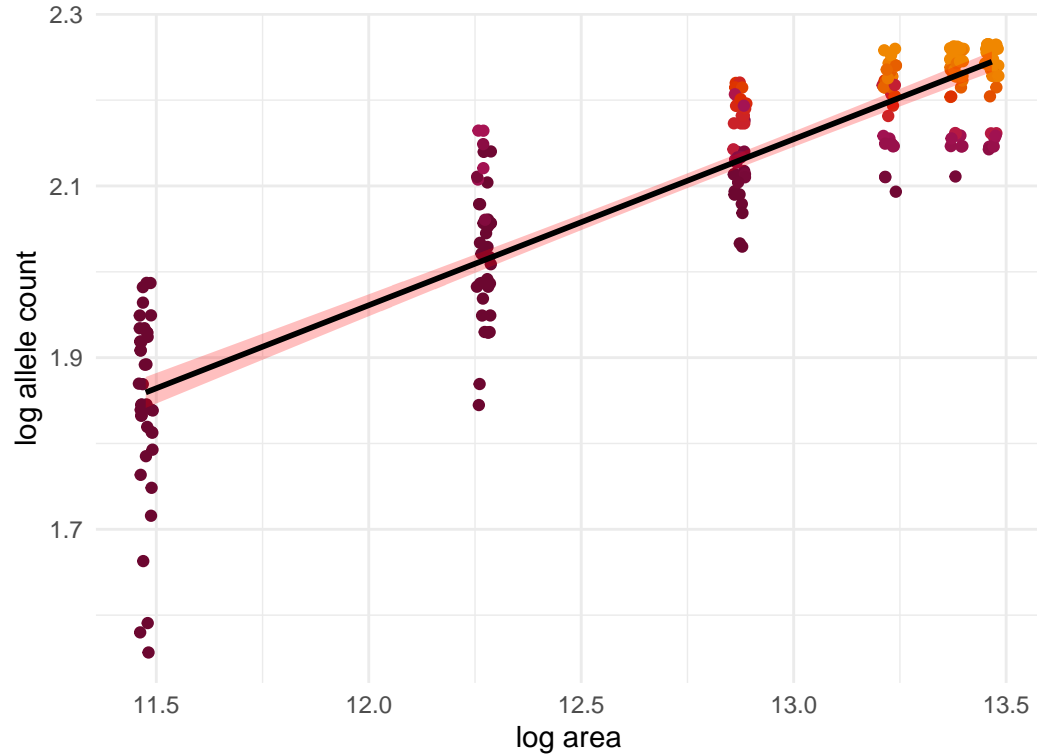
Tamiasciurus douglasii; $z=0.104$



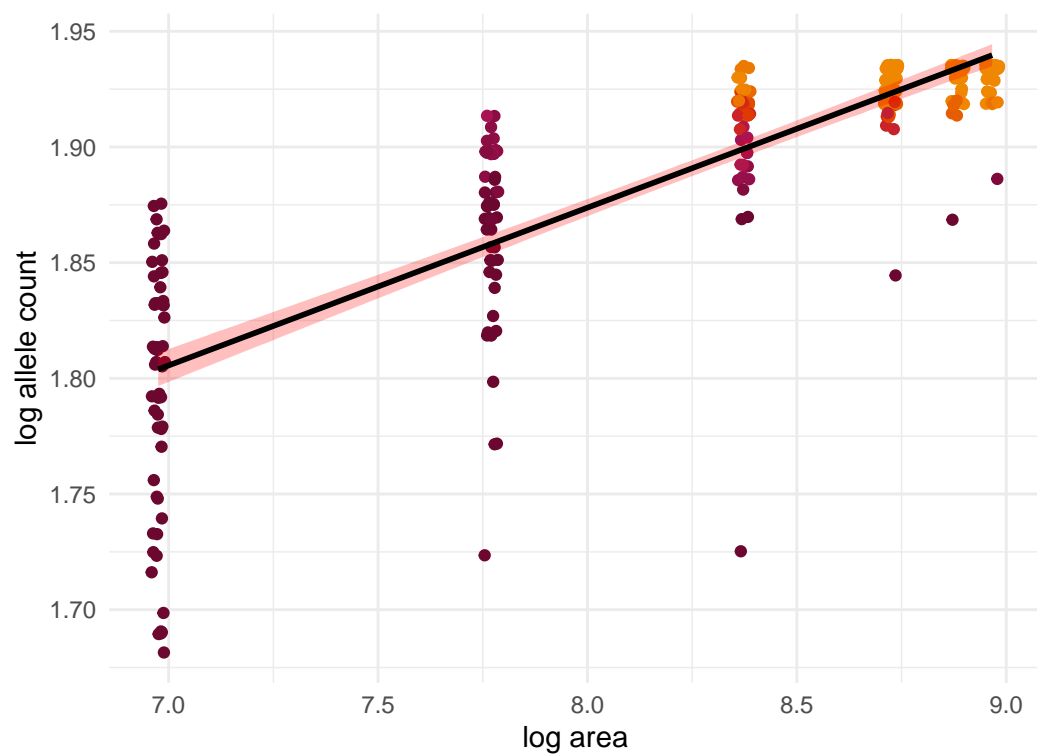
Tamiasciurus hudsonicus; $z=0.116$



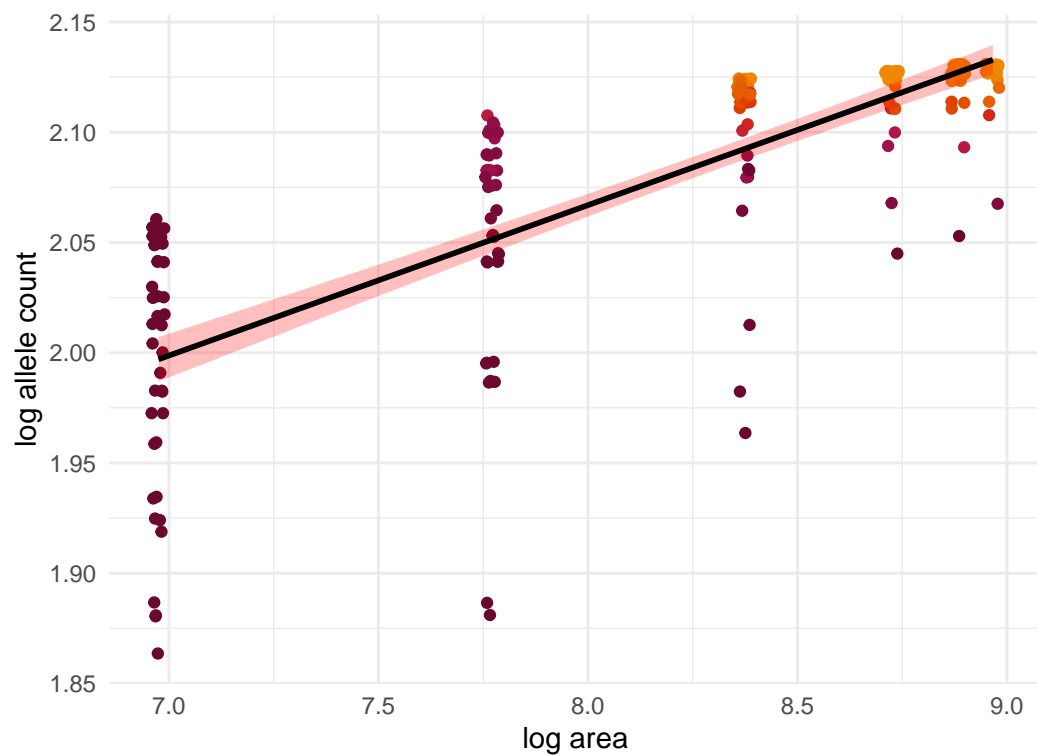
Lepus americanus; $z=0.193$



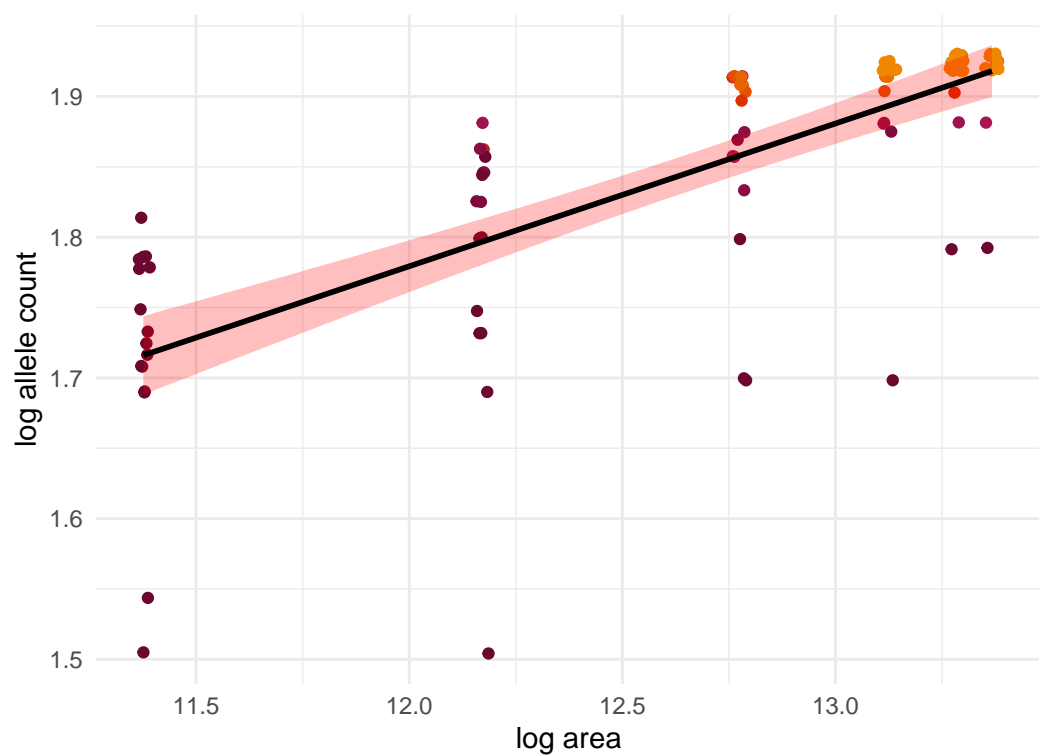
Ambystoma maculatum; $z=0.068$



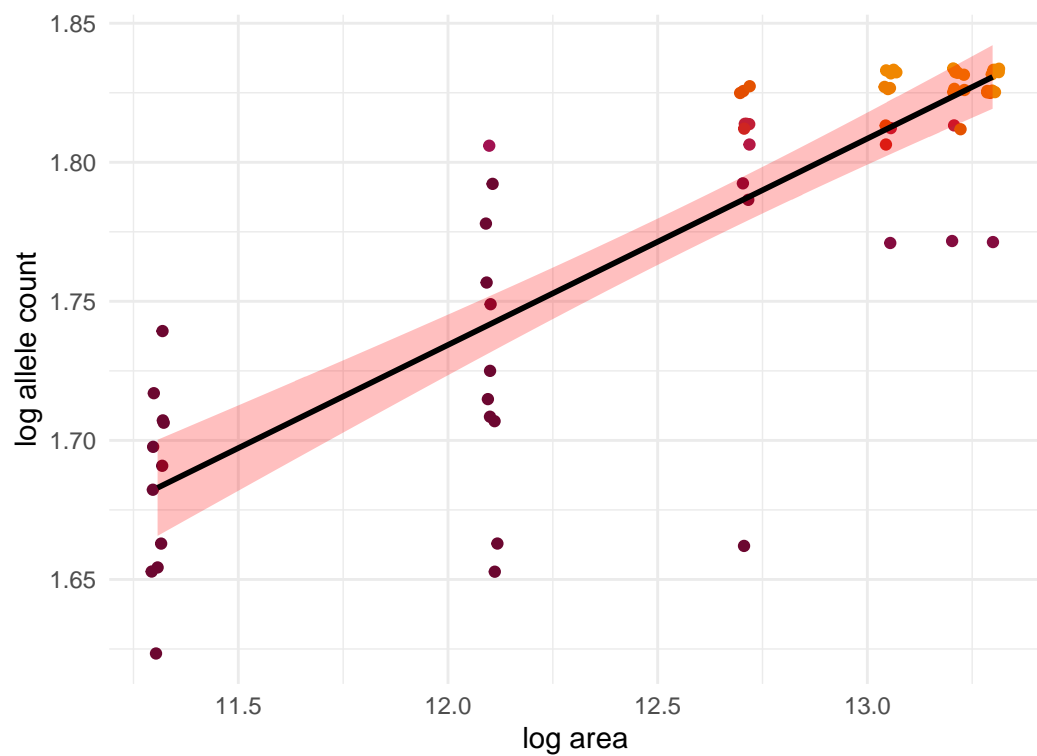
Lithobates sylvaticus; $z=0.068$



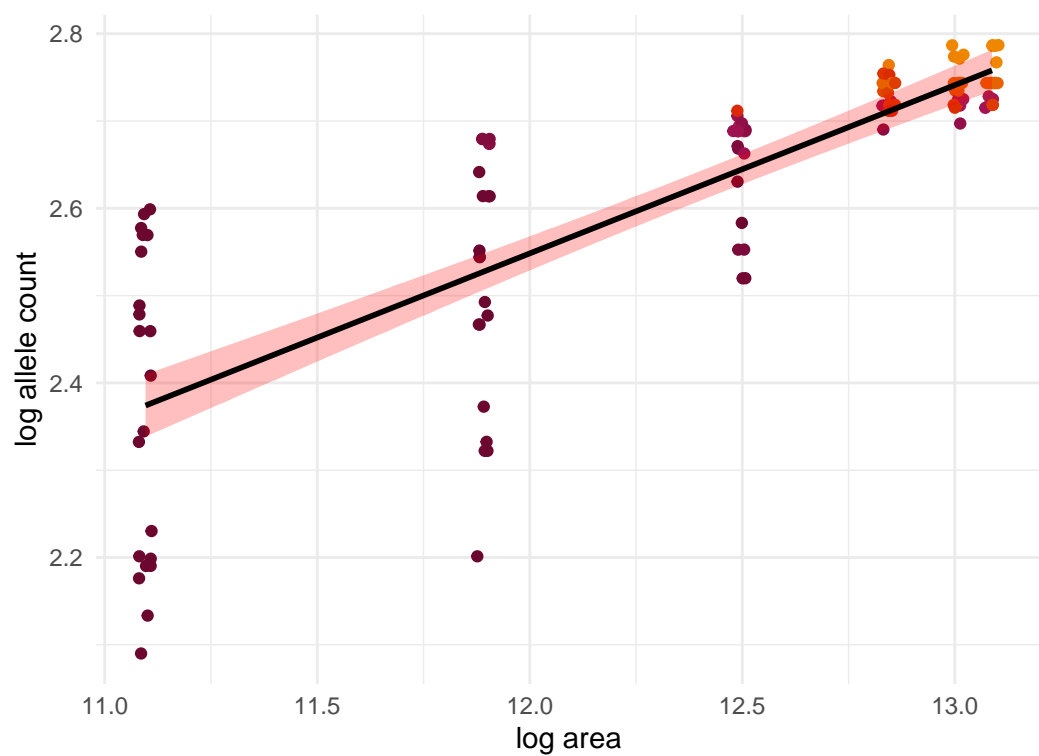
Ursus arctos; $z=0.101$



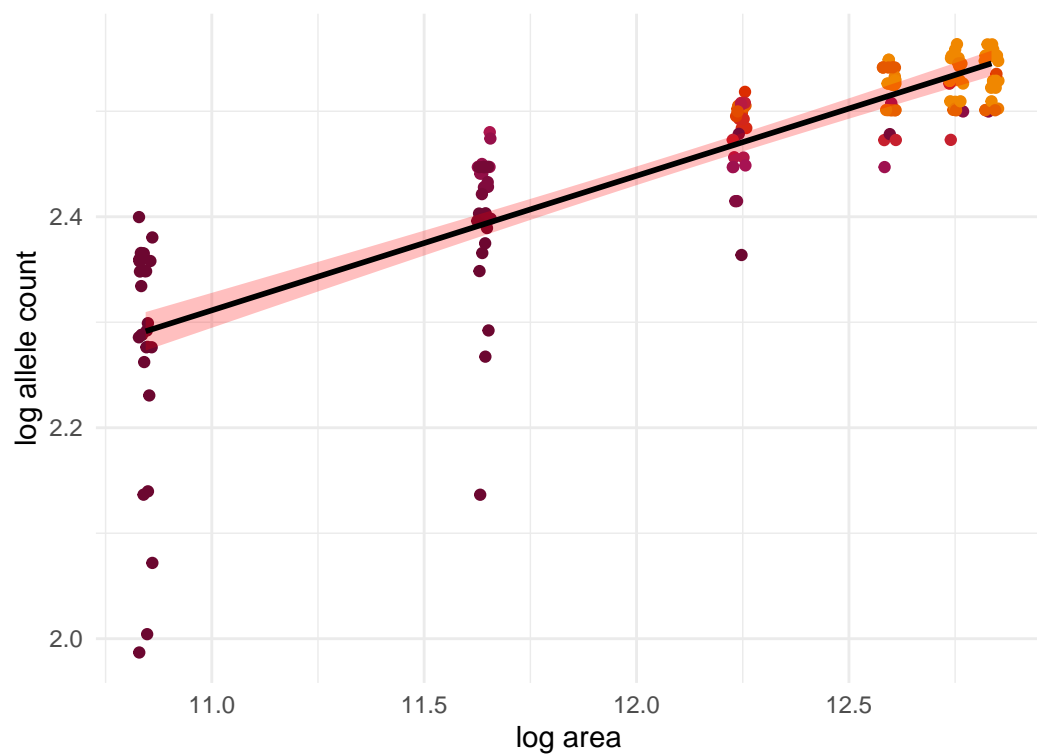
Ursus maritimus; $z=0.074$



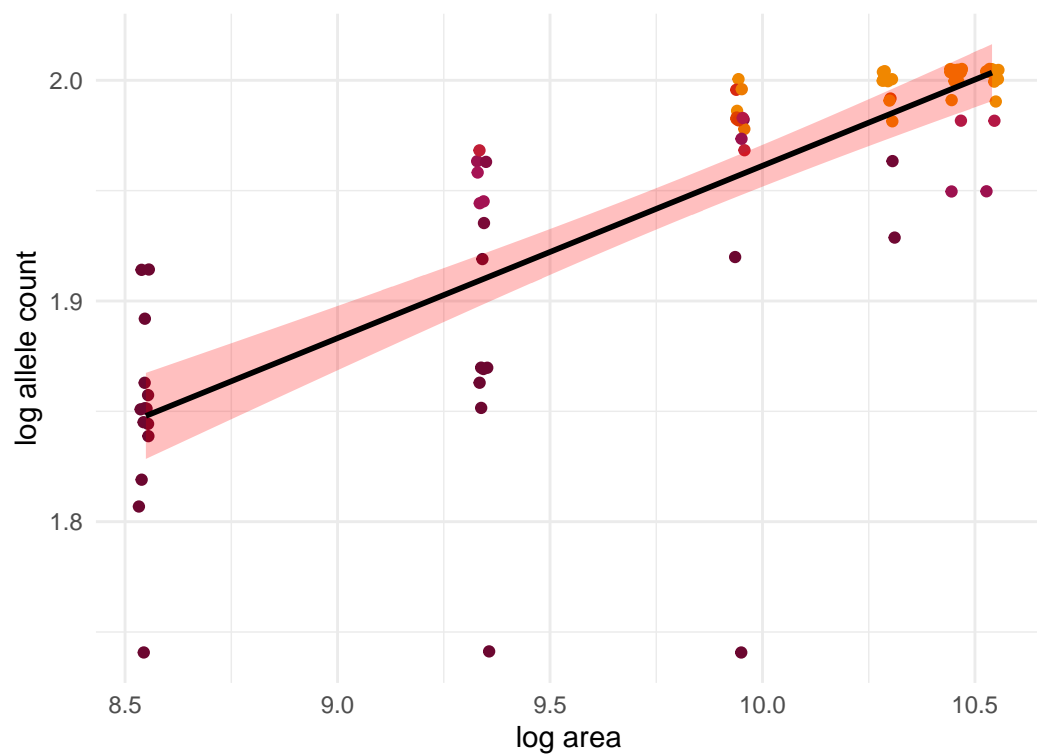
Myotis lucifugus; $z=0.193$



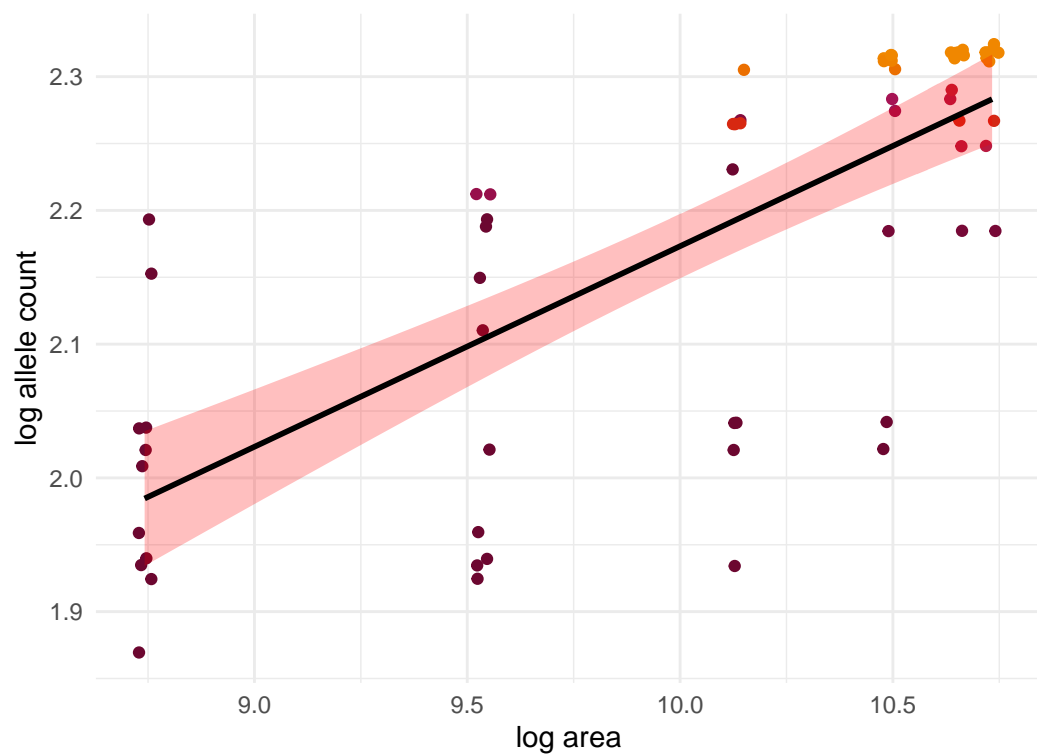
Lithobates sylvaticus; $z=0.128$



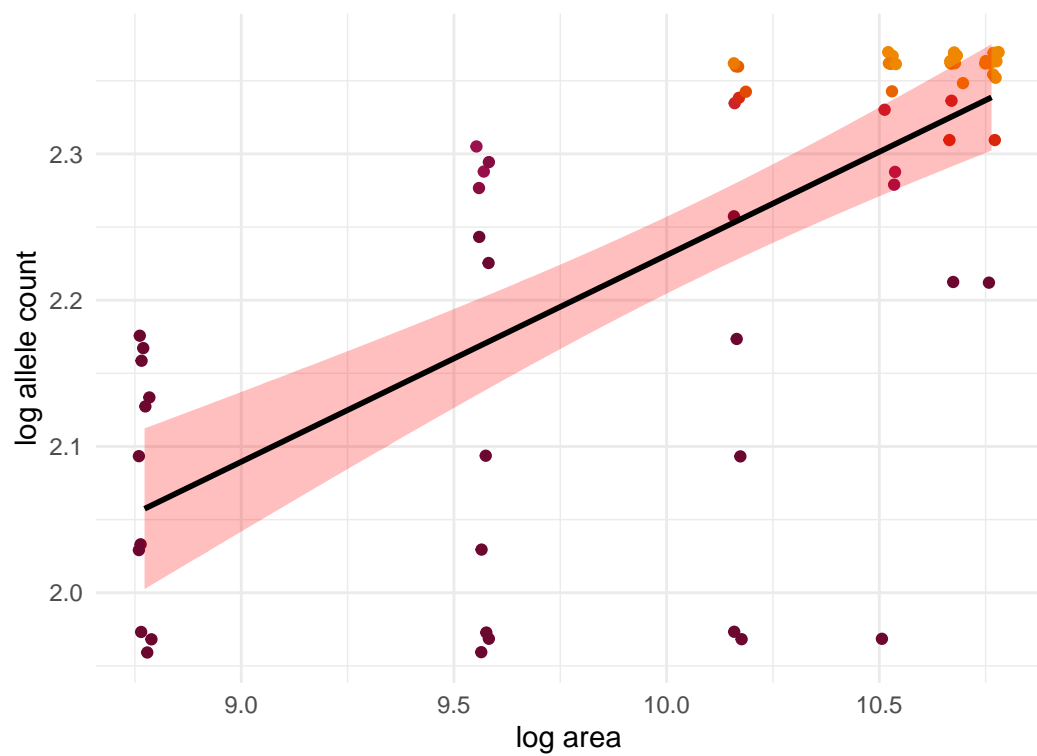
Ovis canadensis; $z=0.078$



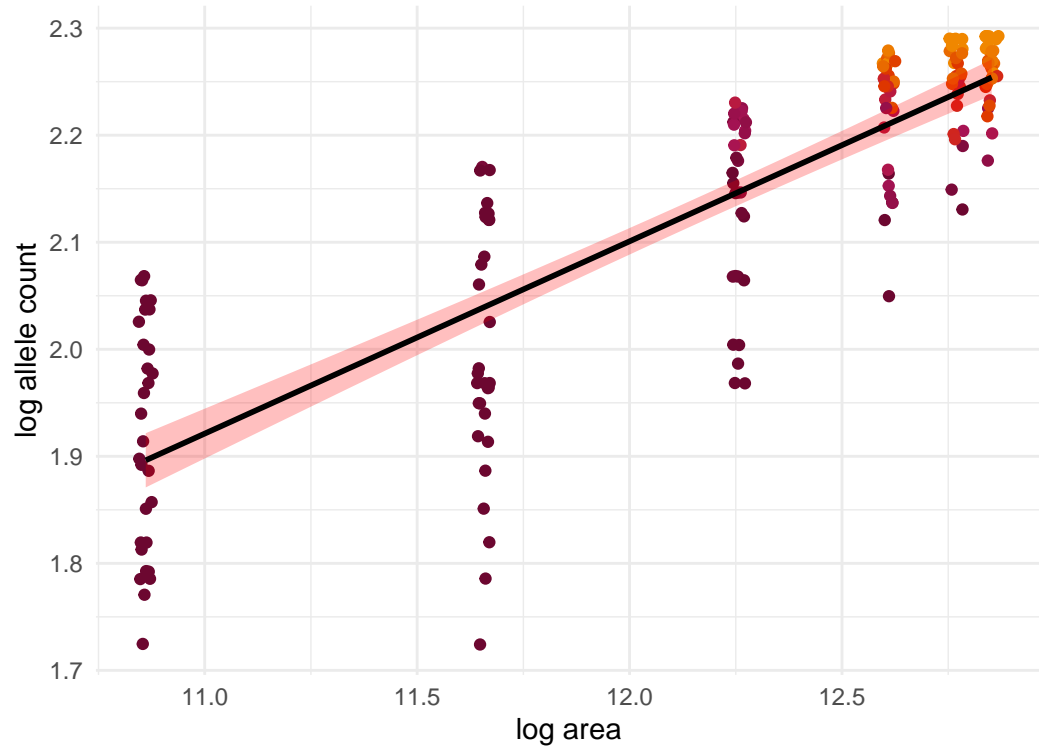
Geospiza fortis; $z=0.15$



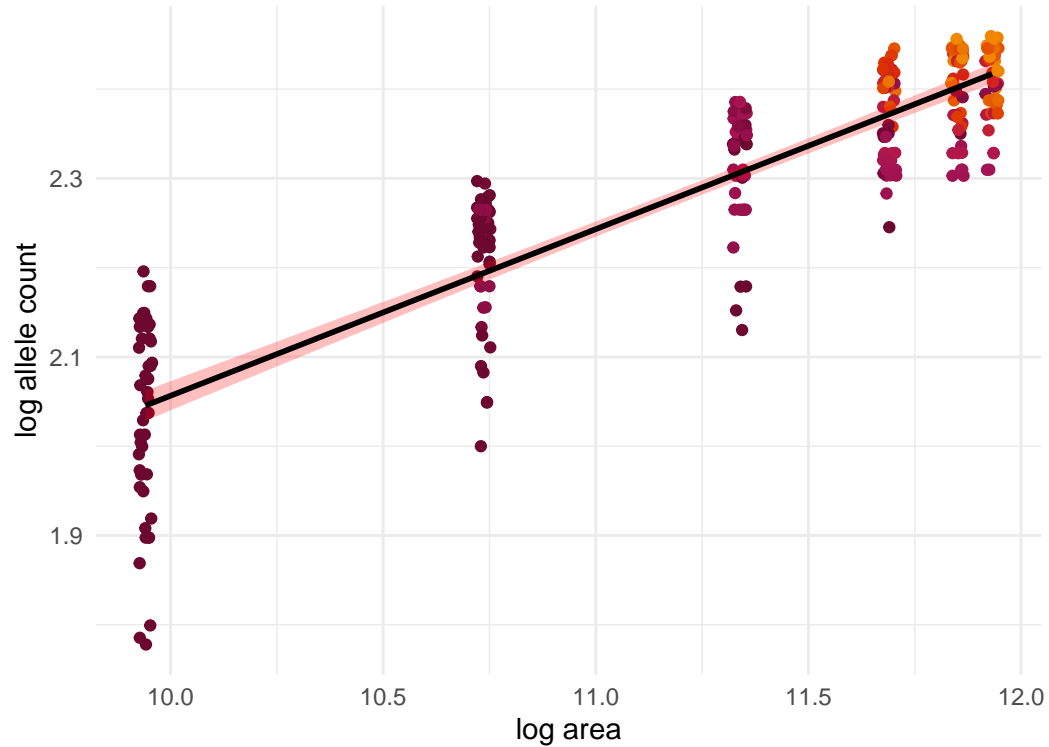
Geospiza fuliginosa; $z=0.141$



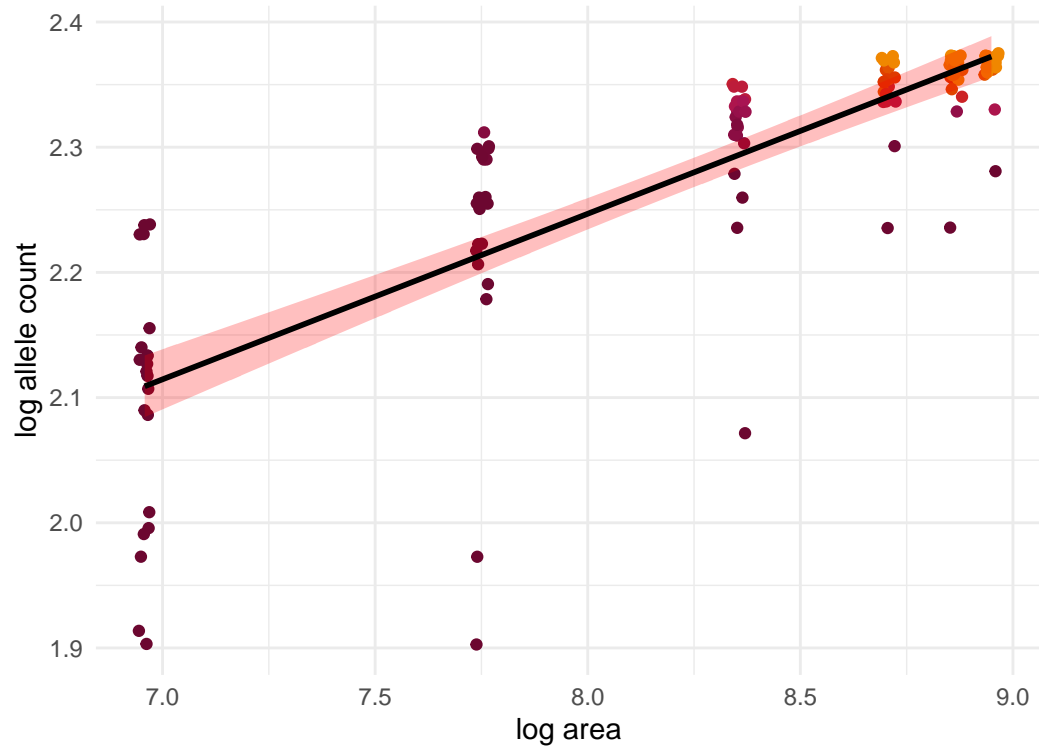
Meles meles; $z=0.18$



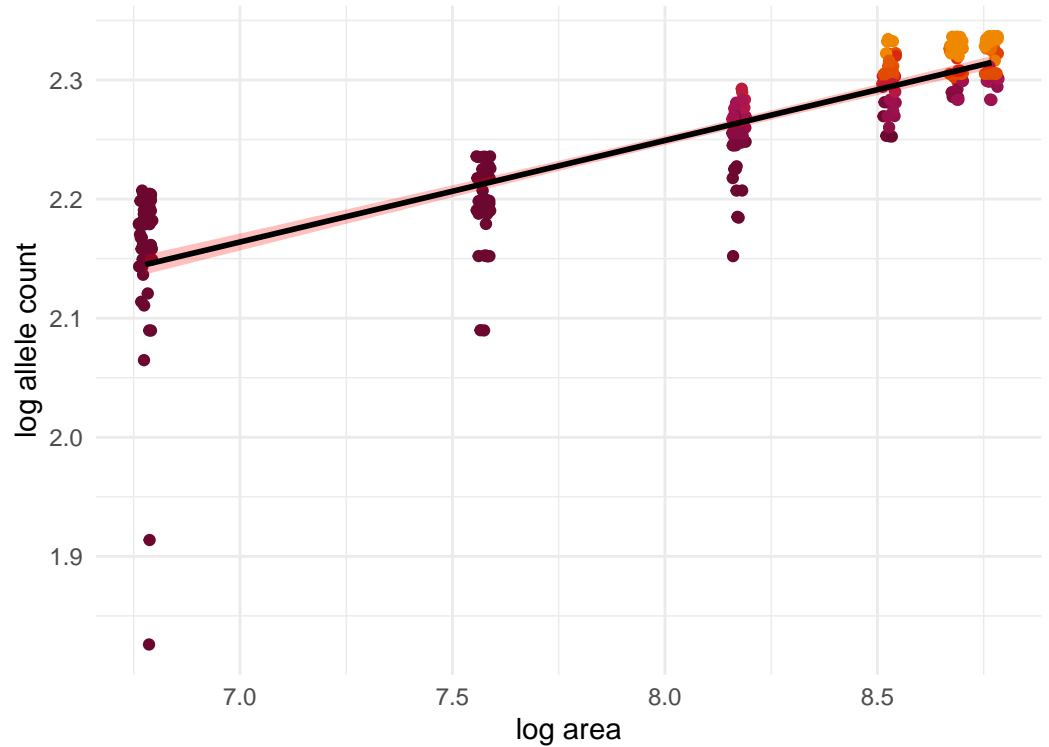
Gopherus polyphemus; $z=0.187$



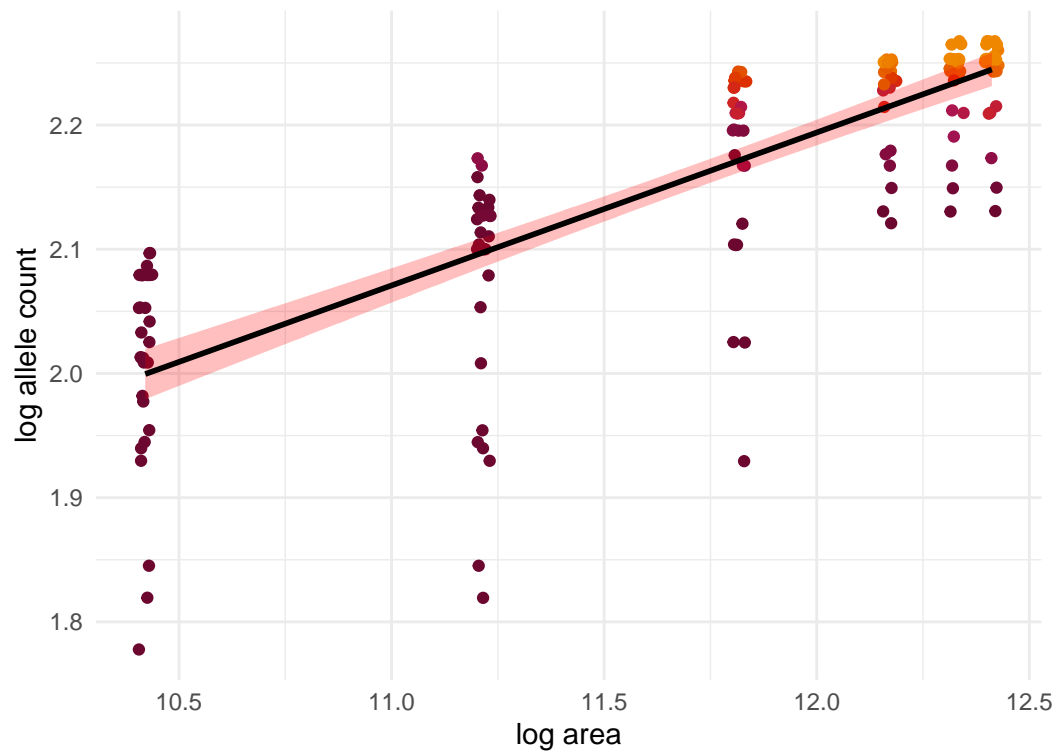
Geospiza fuliginosa; $z=0.132$



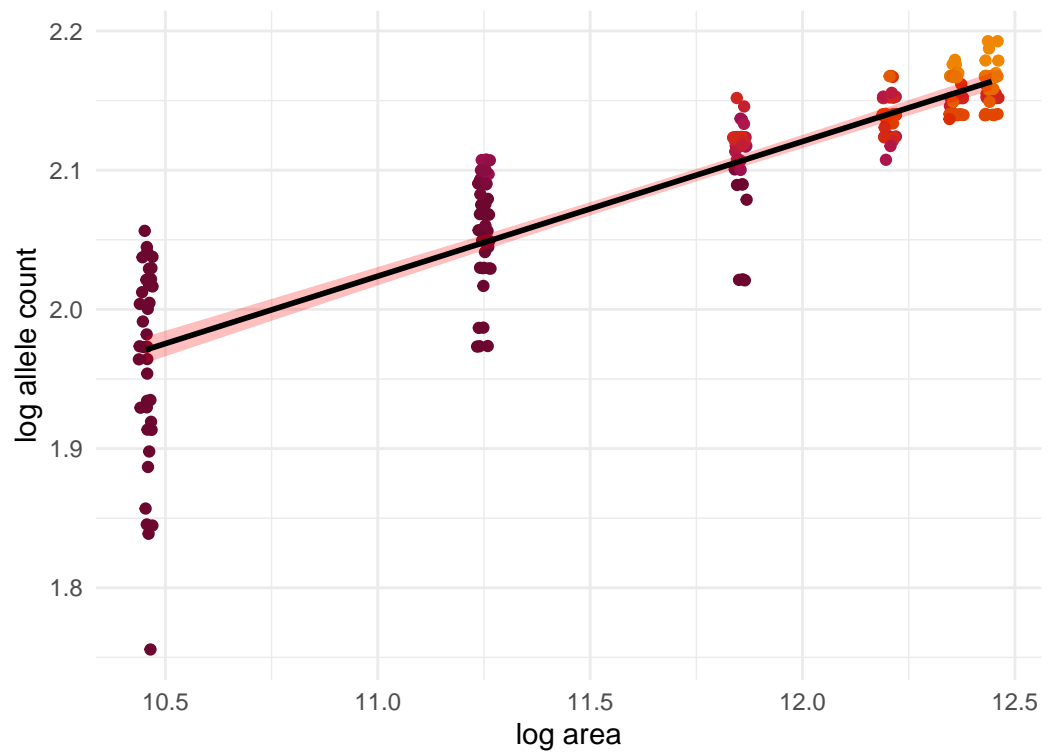
Microtus arvalis; $z=0.085$



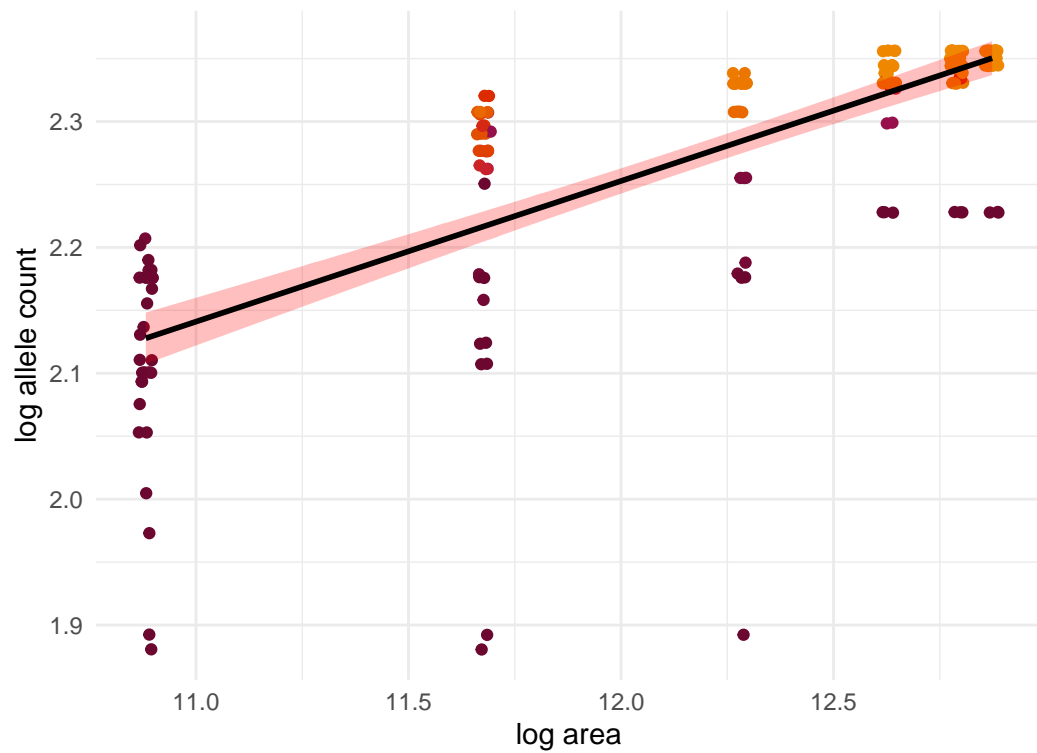
Aphelocoma californica; $z=0.123$



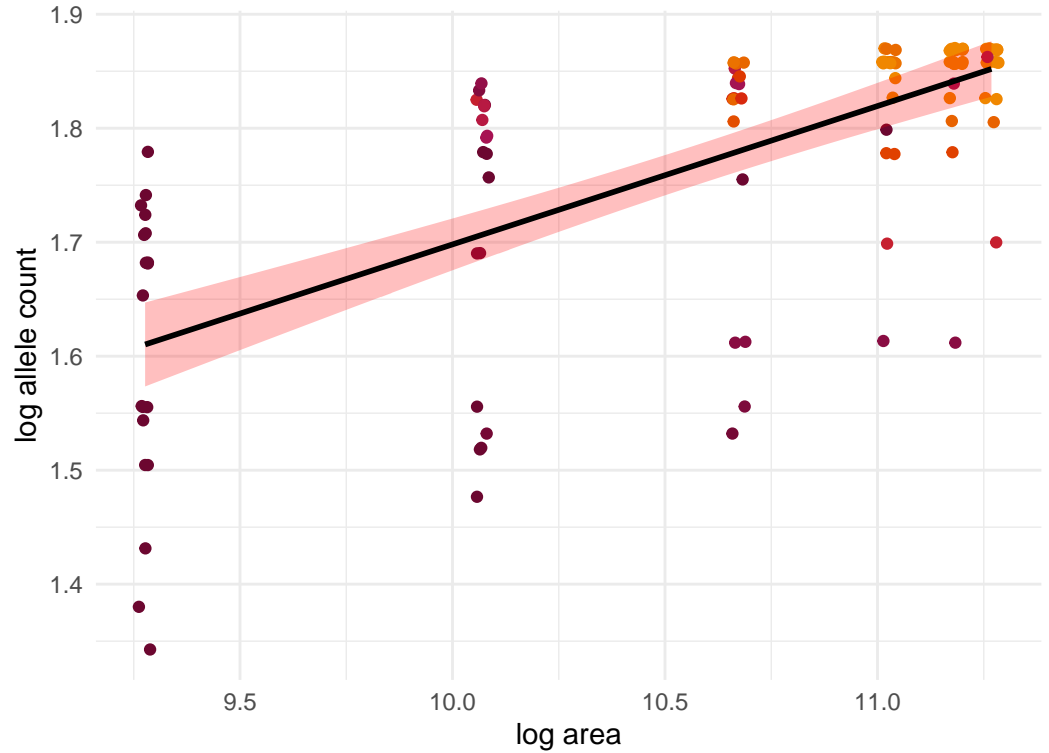
Canis latrans; $z=0.097$



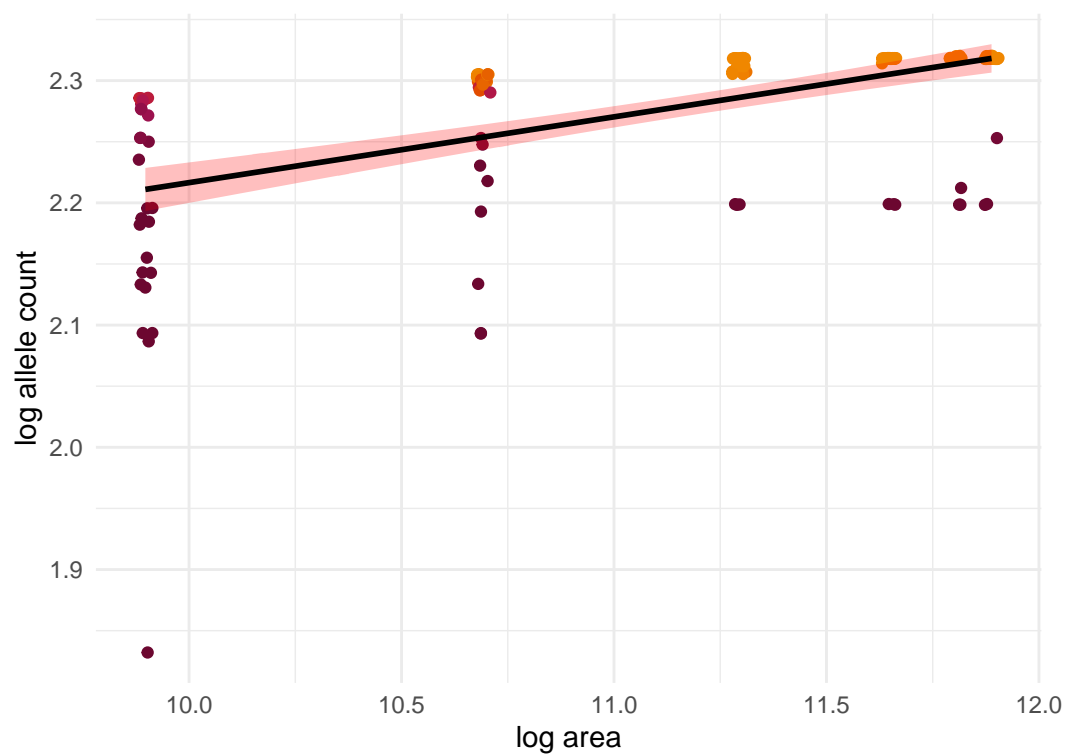
Rousettus aegyptiacus; $z=0.112$



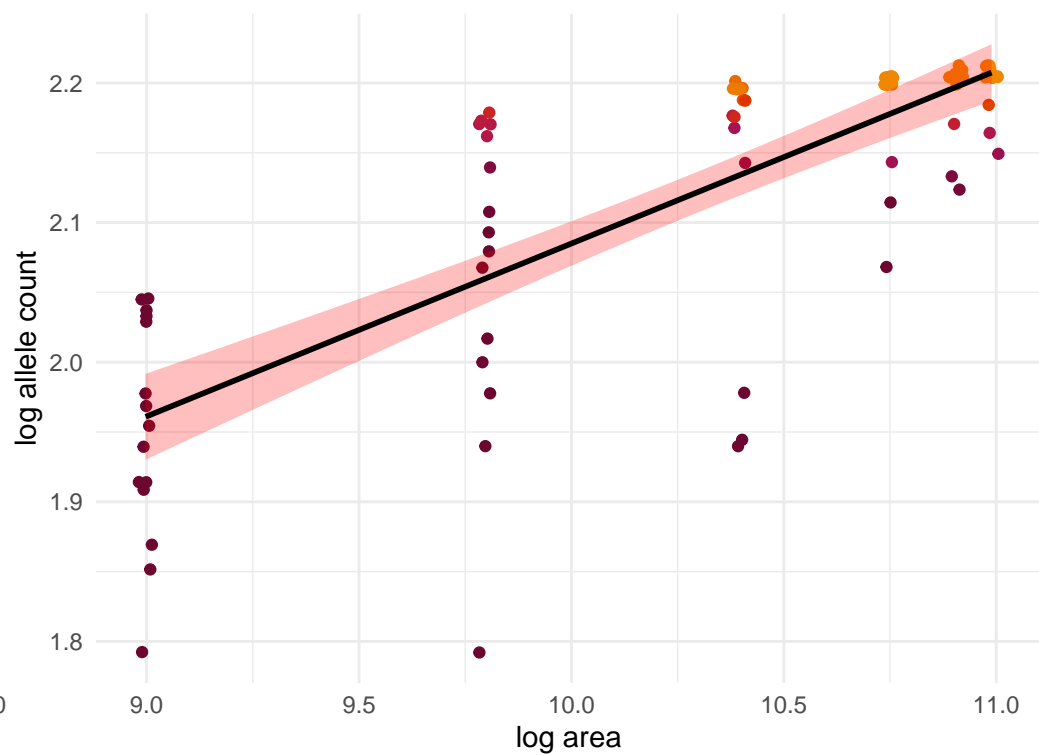
Ambystoma maculatum; $z=0.121$



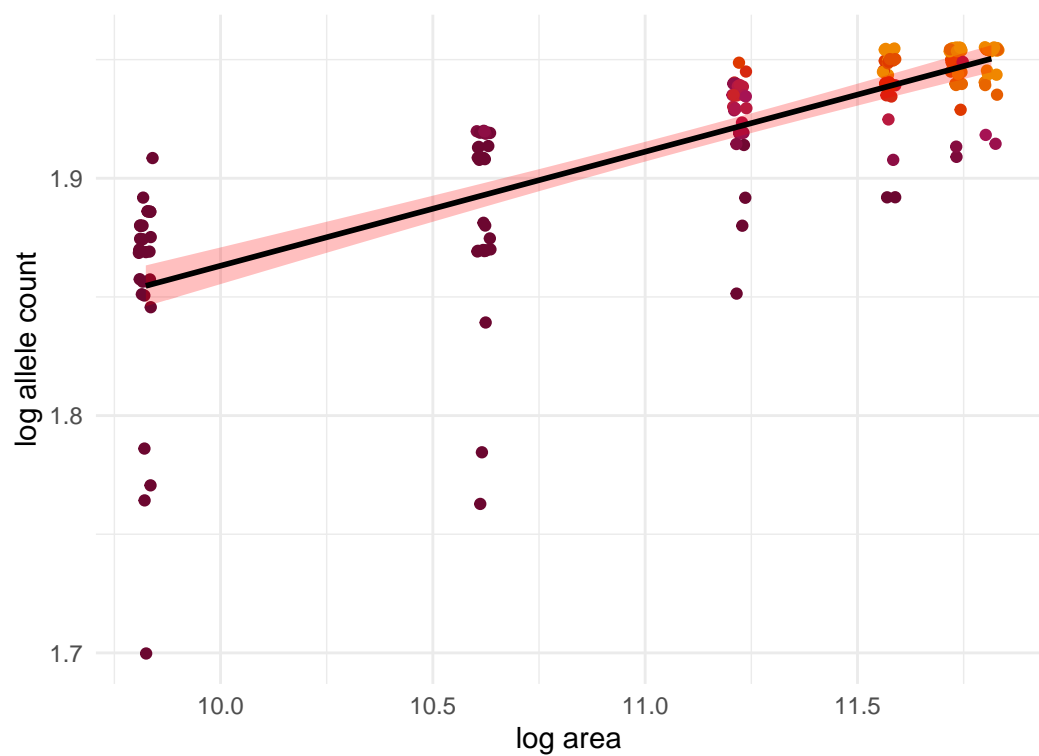
Myotis lucifugus; $z=0.054$



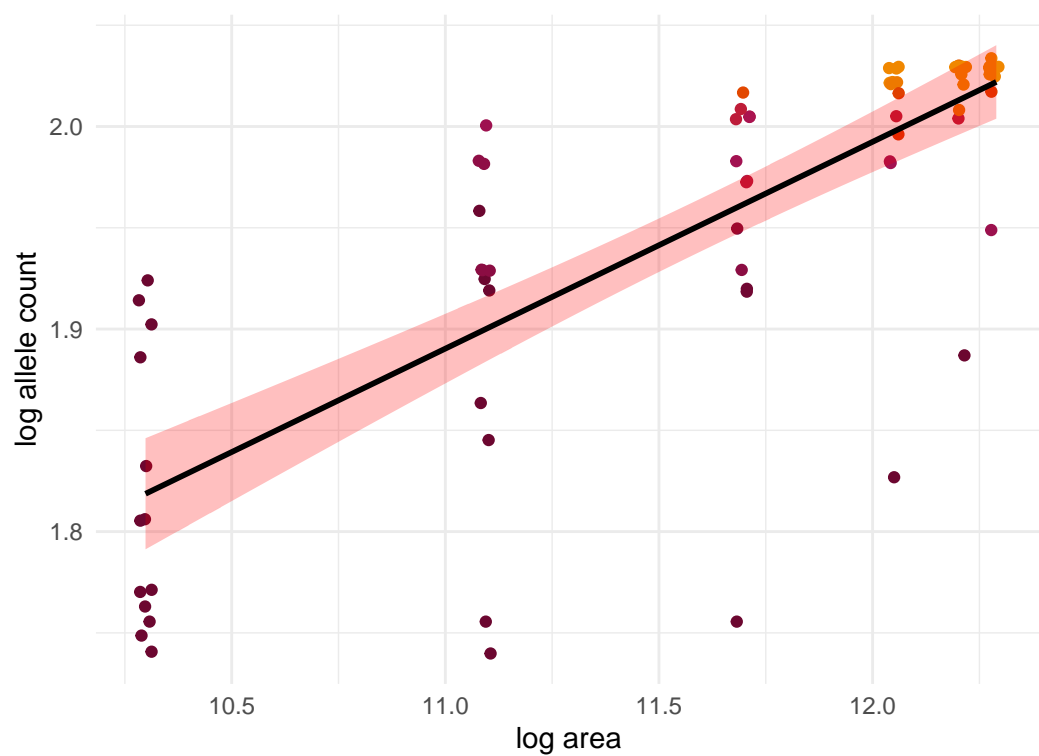
Myotis septentrionalis; $z=0.124$



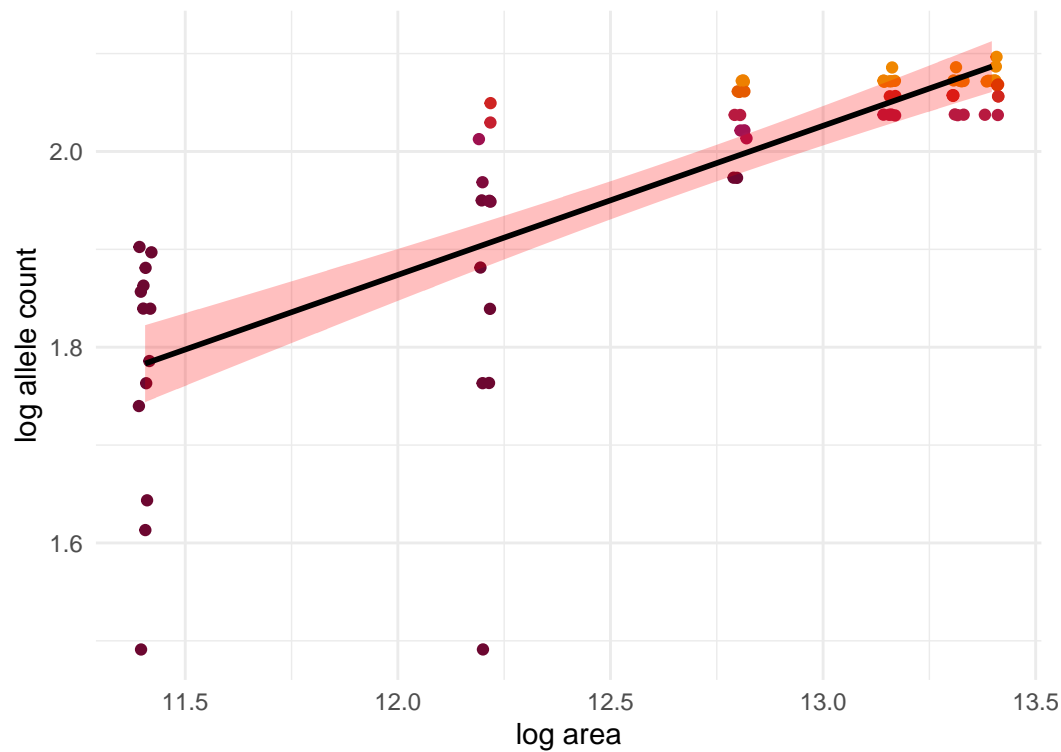
Martes americana; $z=0.048$



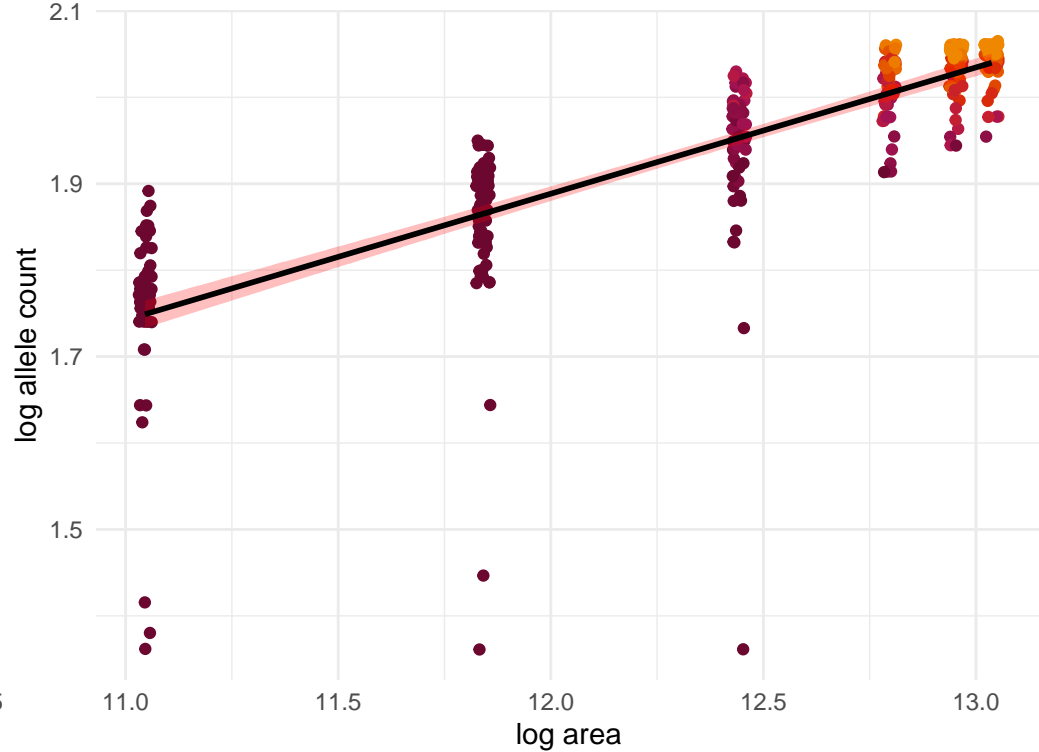
Lemmus lemmus; $z=0.102$



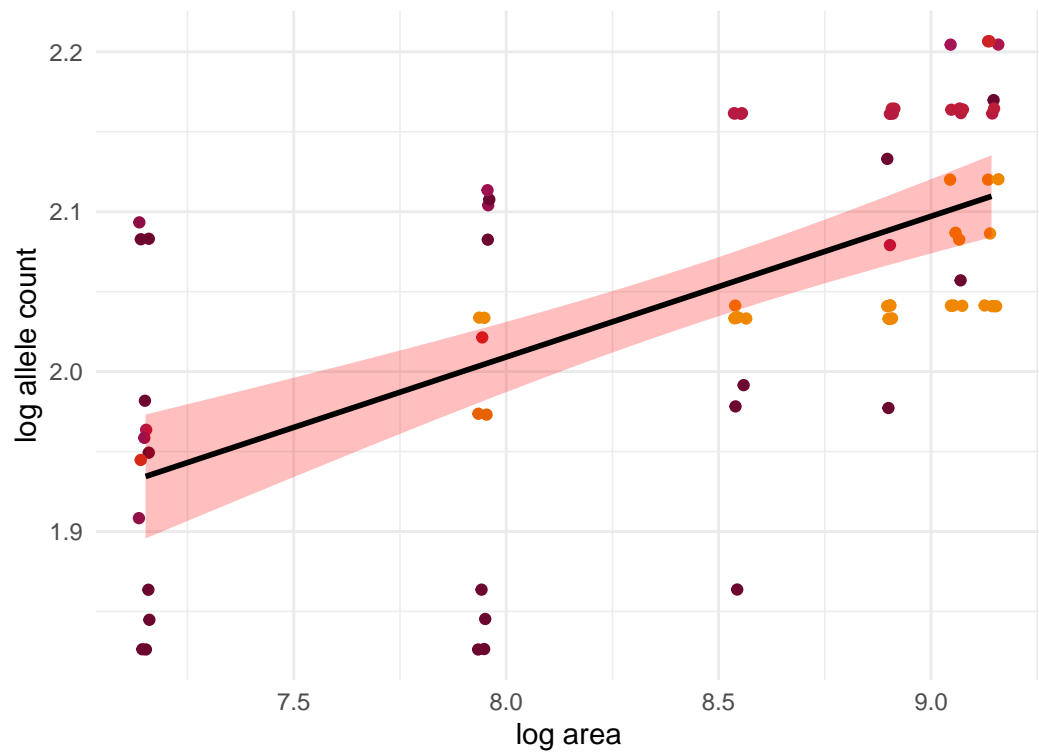
Poecile hudsonicus; $z=0.152$



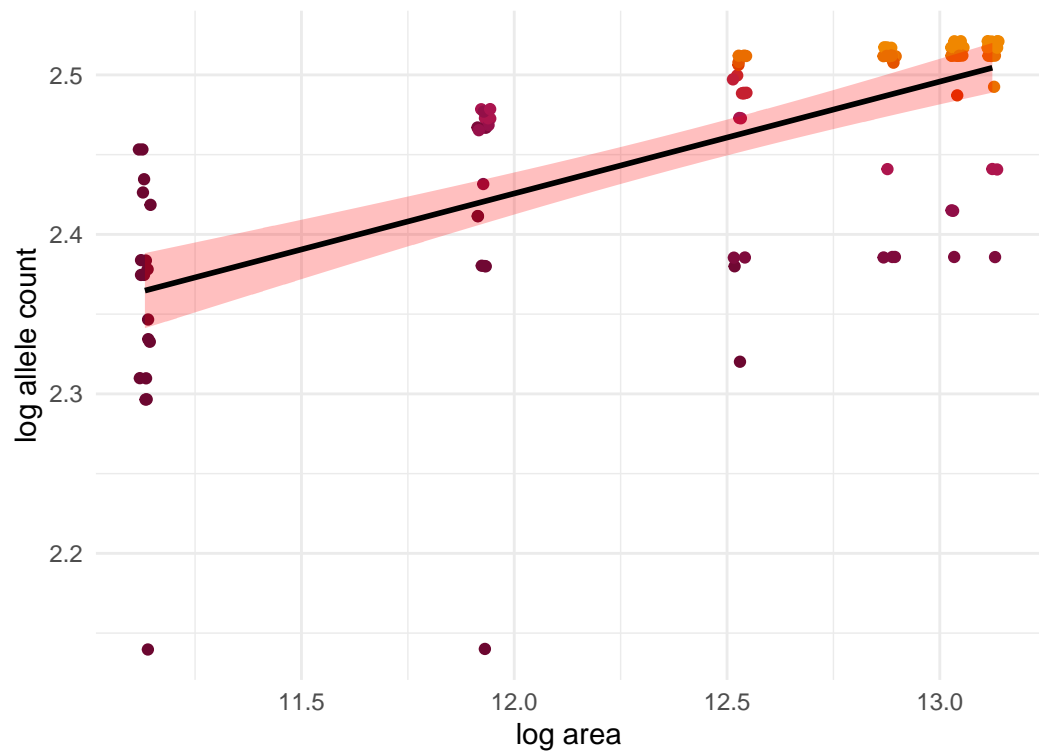
Odocoileus hemionus; $z=0.146$



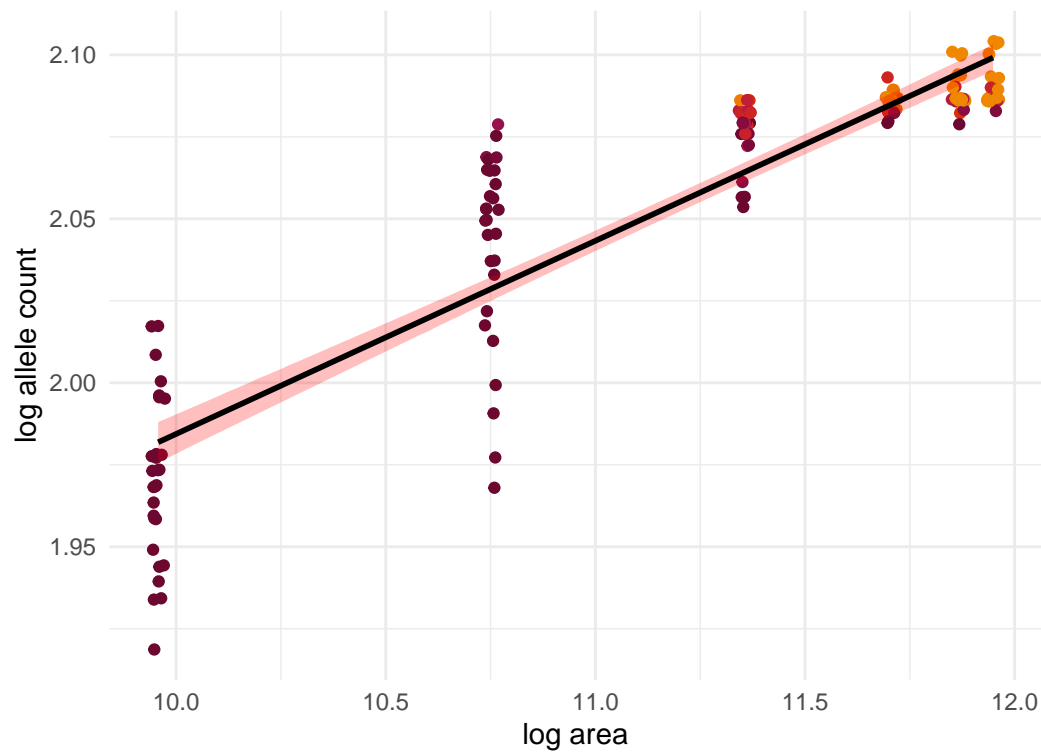
Amblyrhynchus cristatus; $z=0.088$



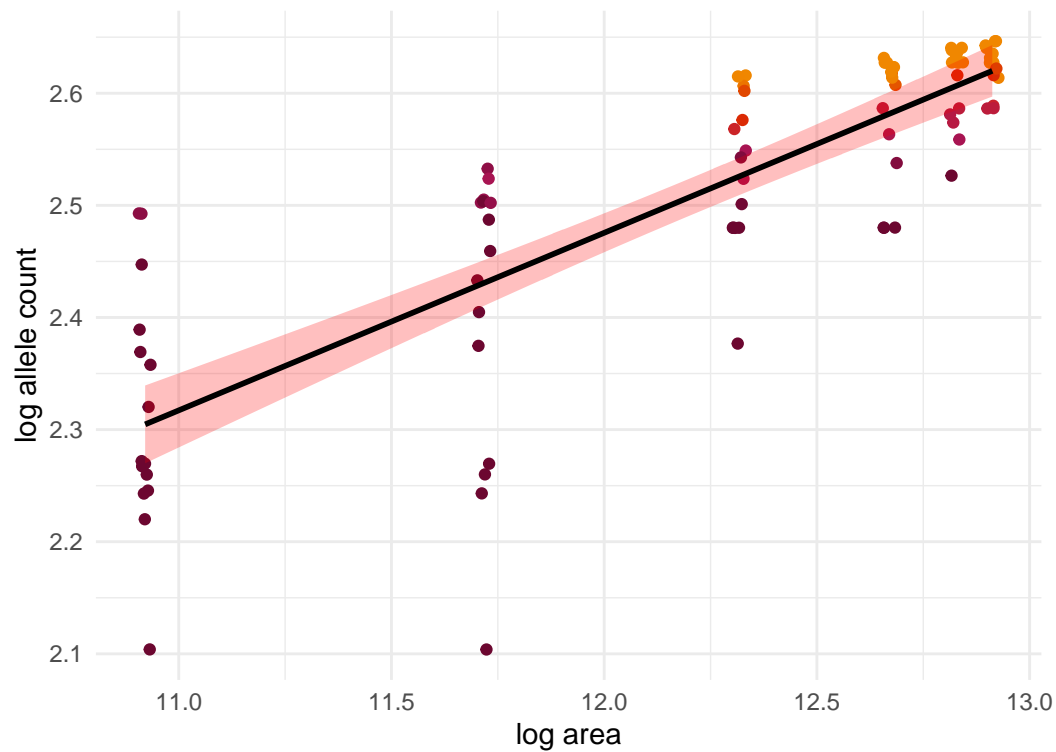
Rangifer tarandus; $z=0.07$



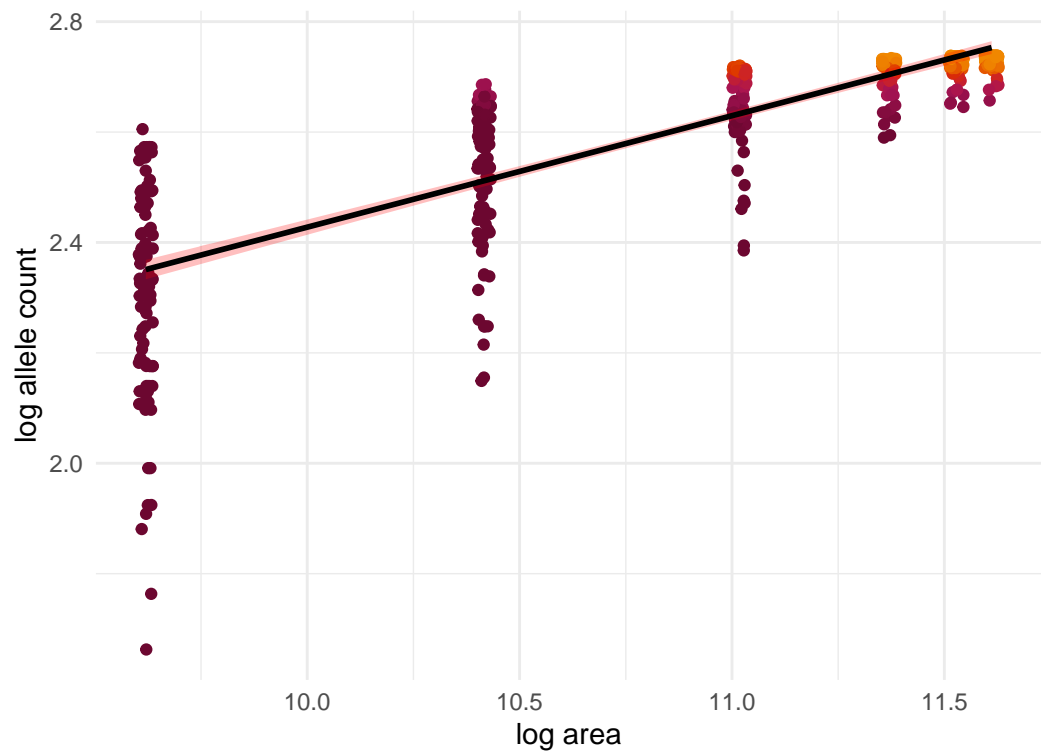
Lynx canadensis; $z=0.059$



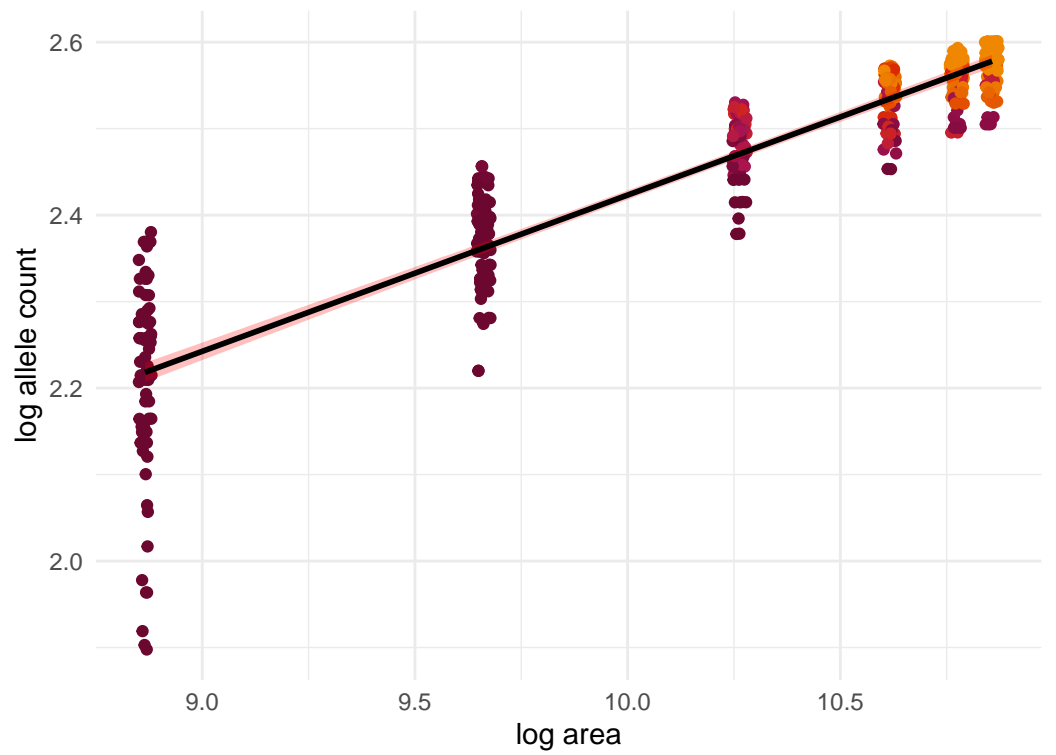
Felis silvestris; $z=0.158$



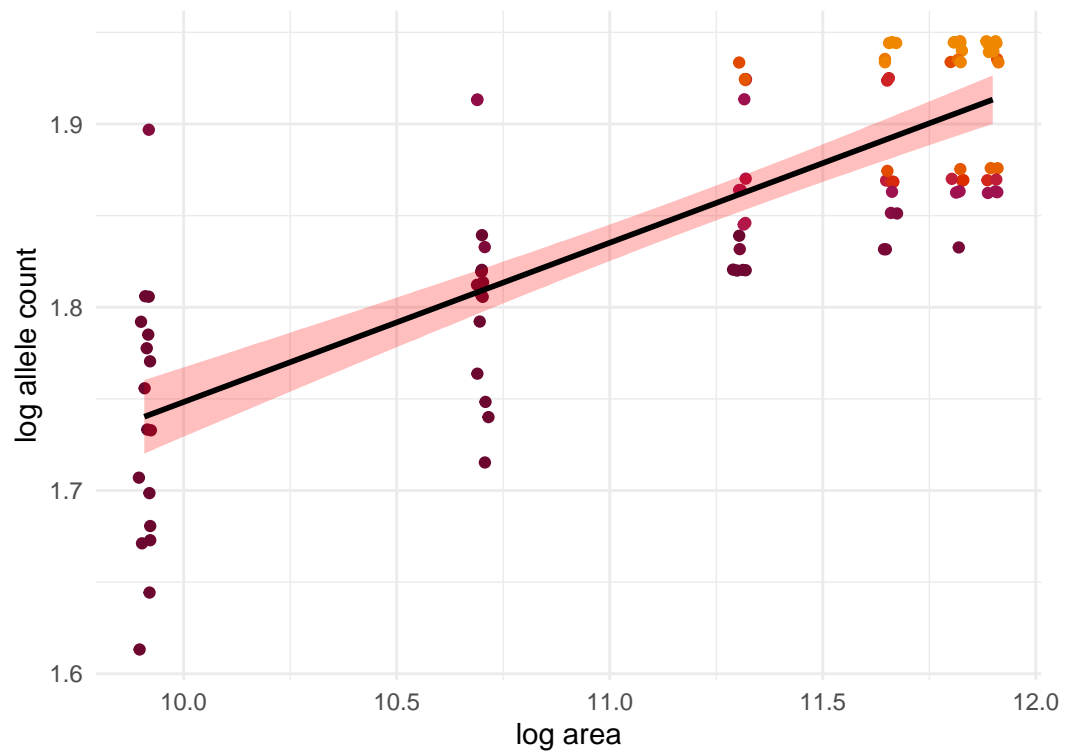
Ascapus montanus; $z=0.202$



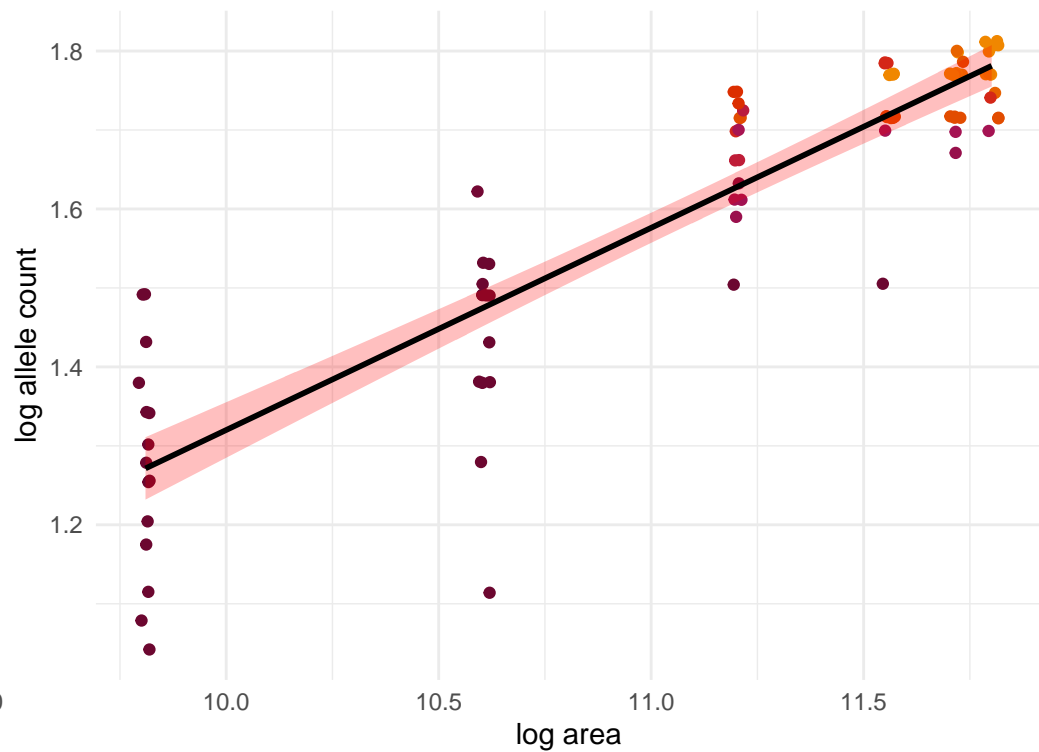
Ambystoma barbouri; $z=0.181$



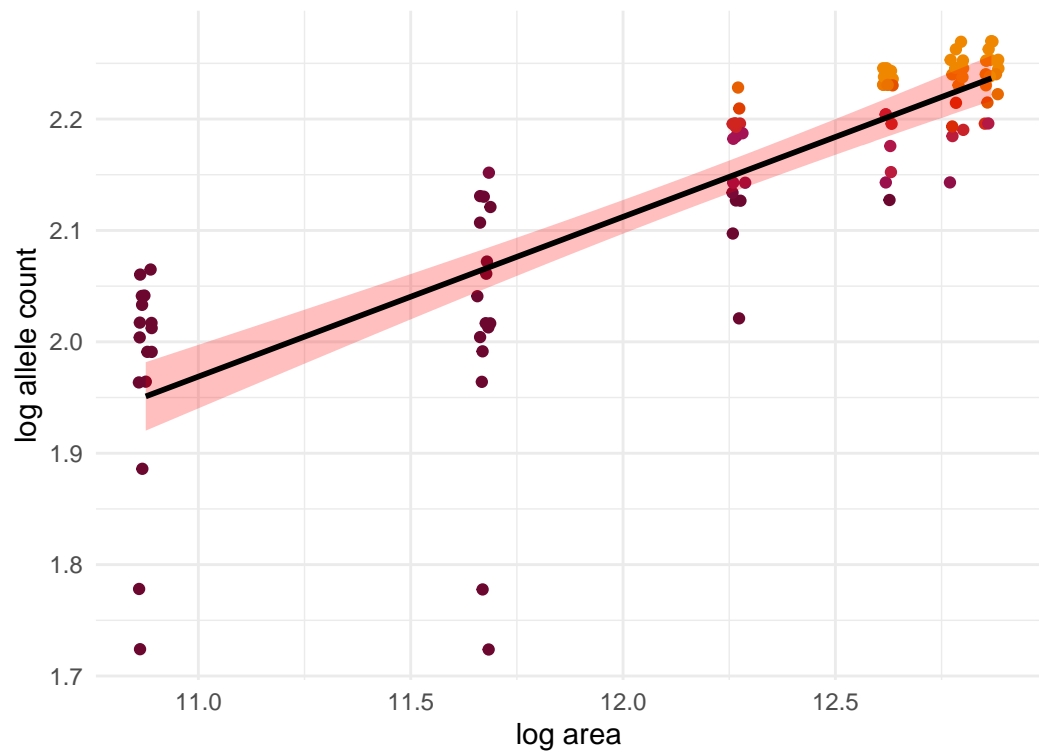
Strix occidentalis; $z=0.087$



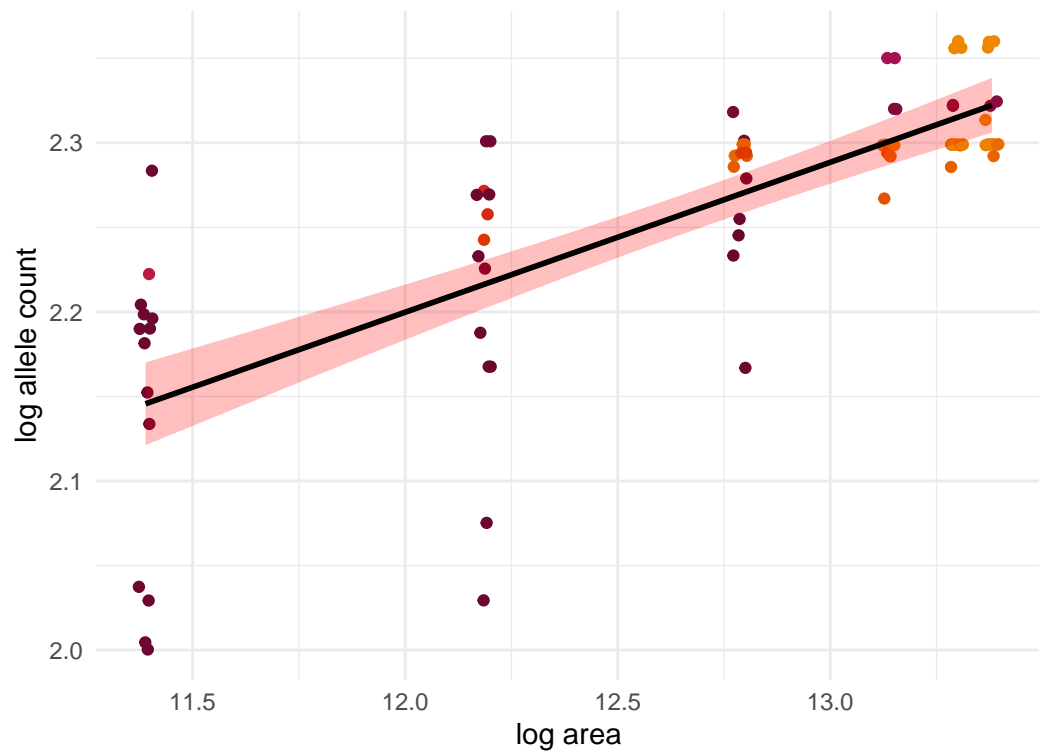
Liolaemus tenuis; $z=0.256$



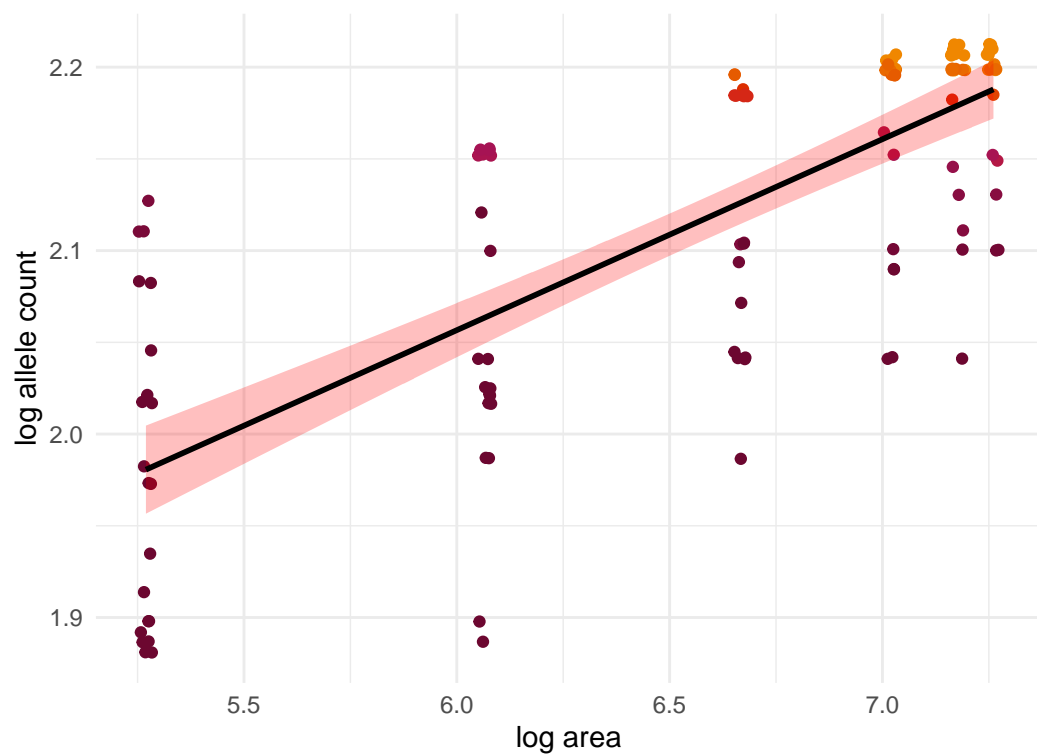
Alces alces; $z=0.143$



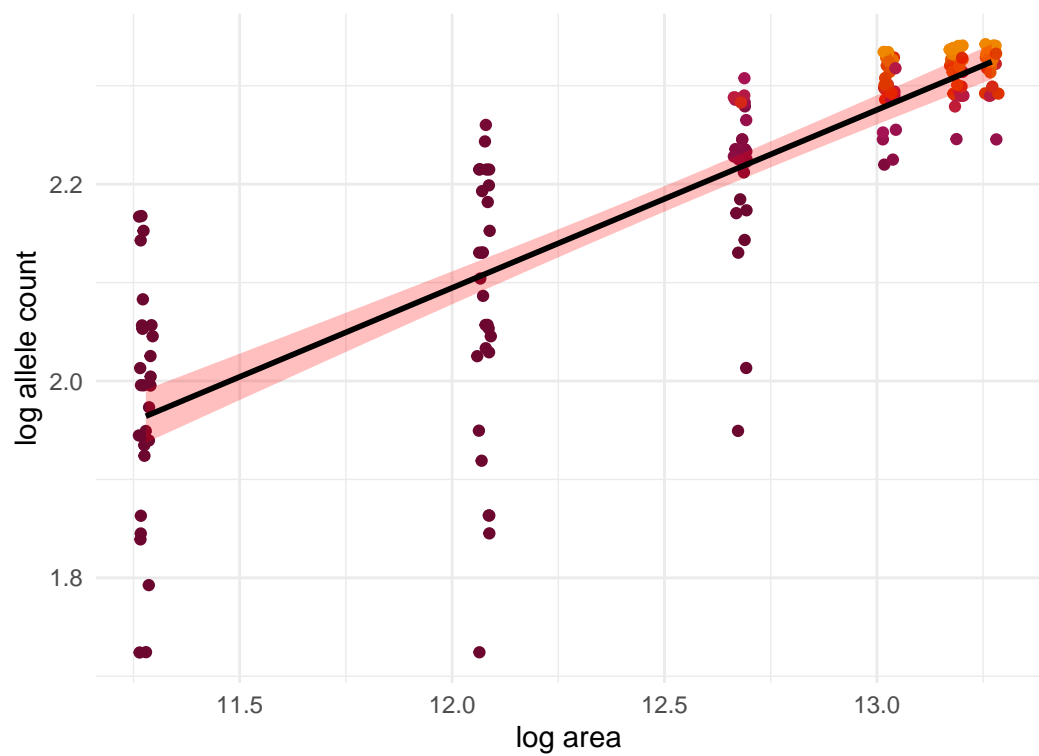
Ursus maritimus; $z=0.089$



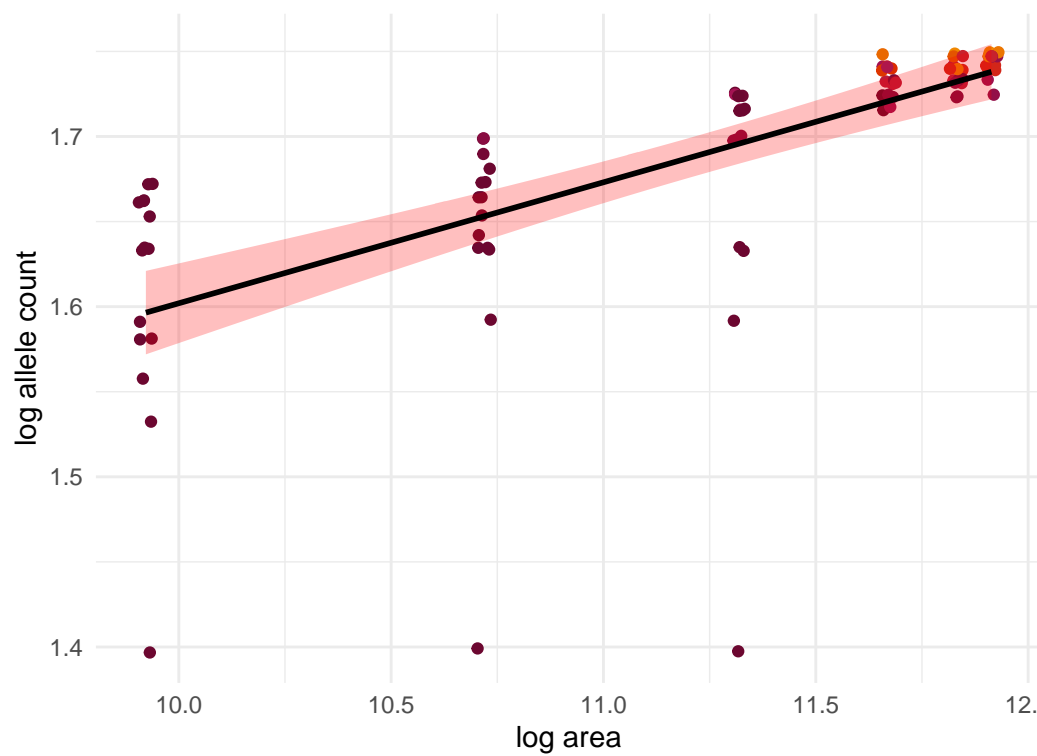
Plethodon albagula; $z=0.104$



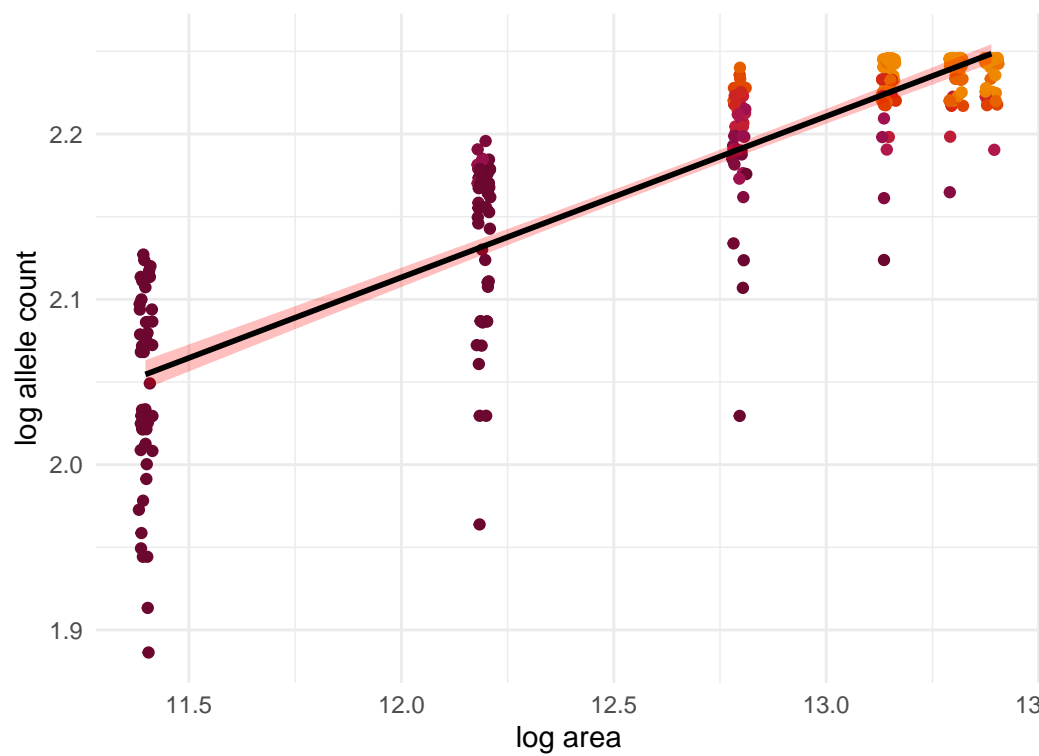
Ursus americanus; $z=0.181$



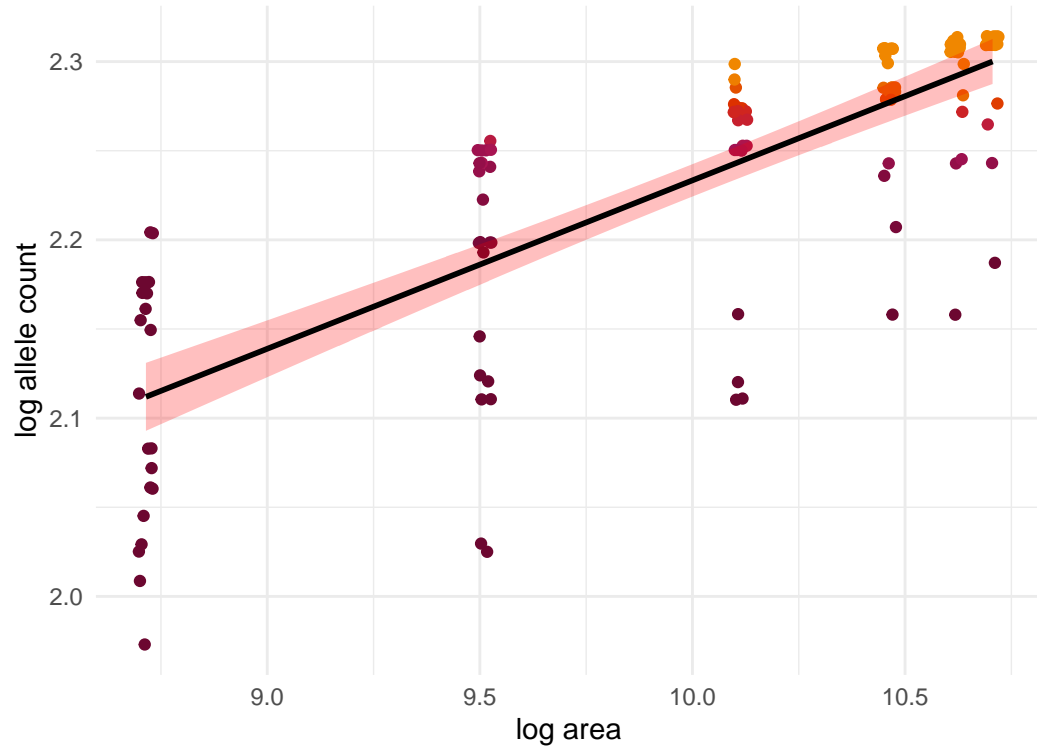
Myotis escaleraei; $z=0.071$



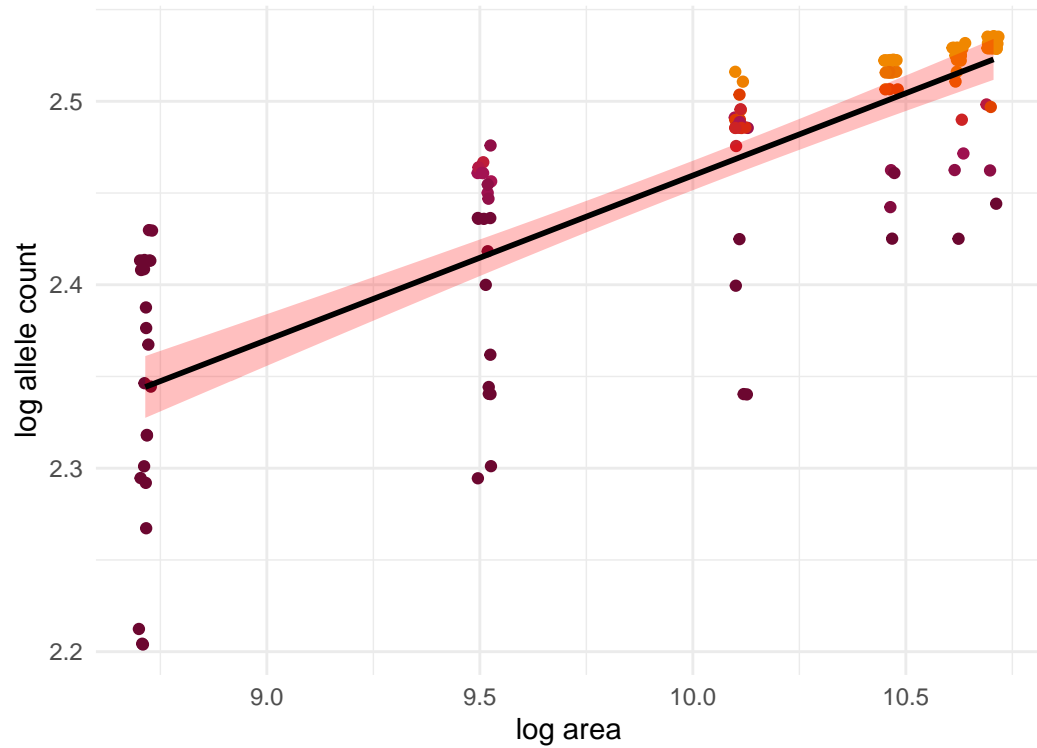
Lynx rufus; $z=0.097$



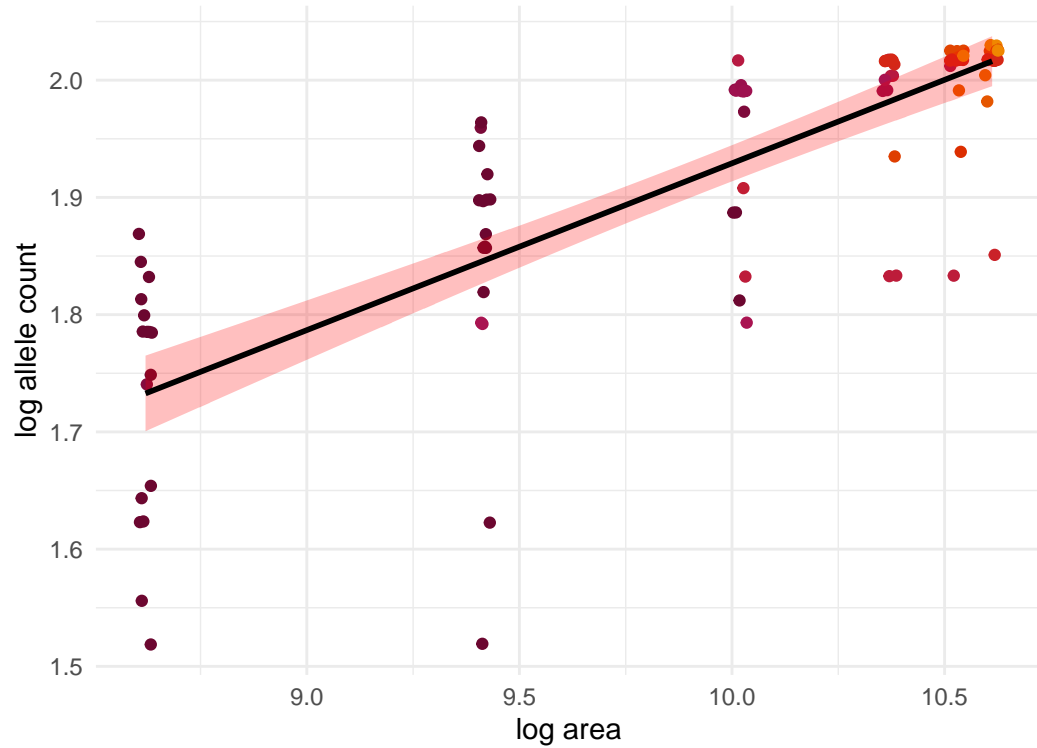
Ambystoma maculatum; $z=0.094$



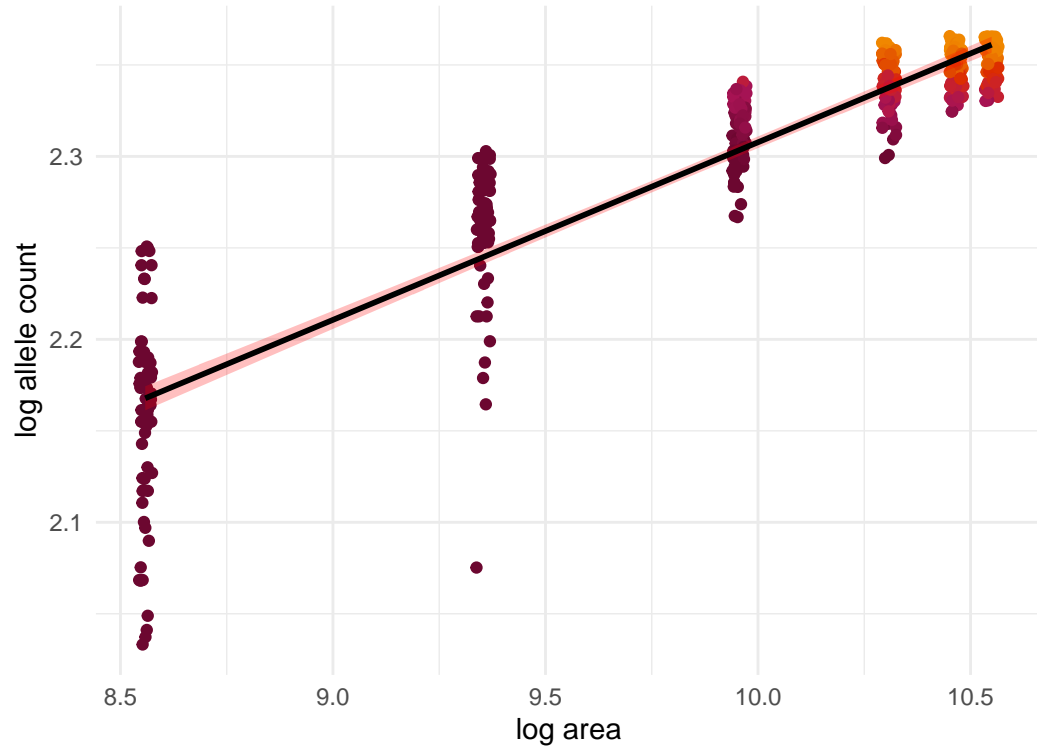
Rana sylvatica; $z=0.09$



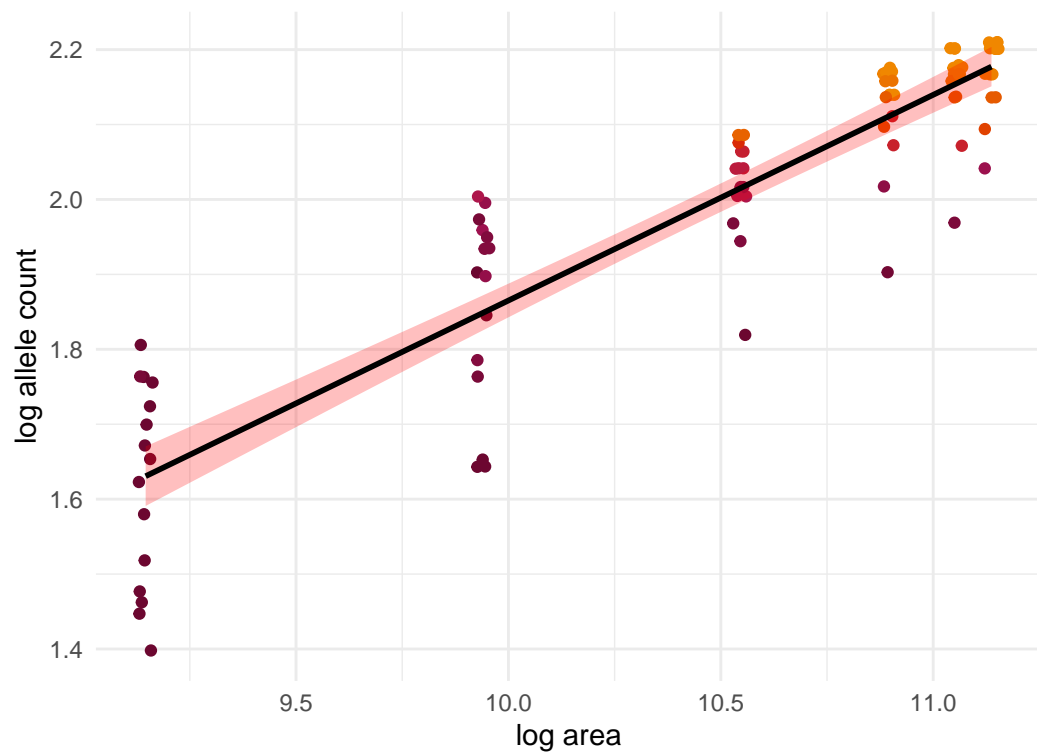
Rana draytonii; $z=0.142$



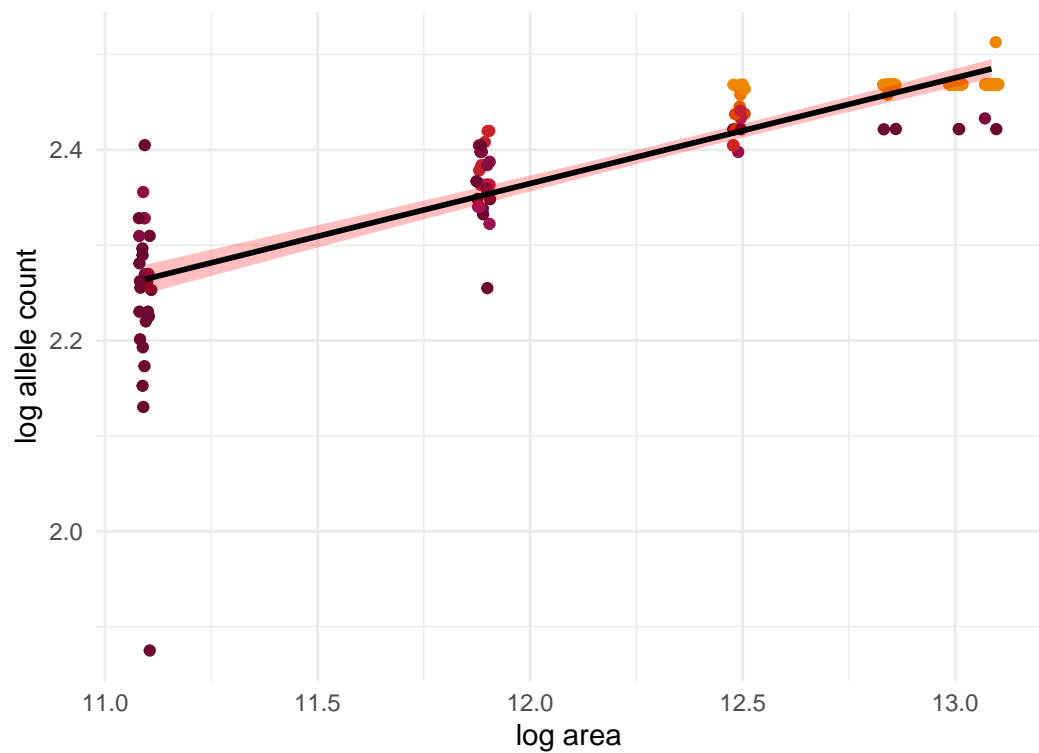
Odocoileus virginianus; $z=0.097$



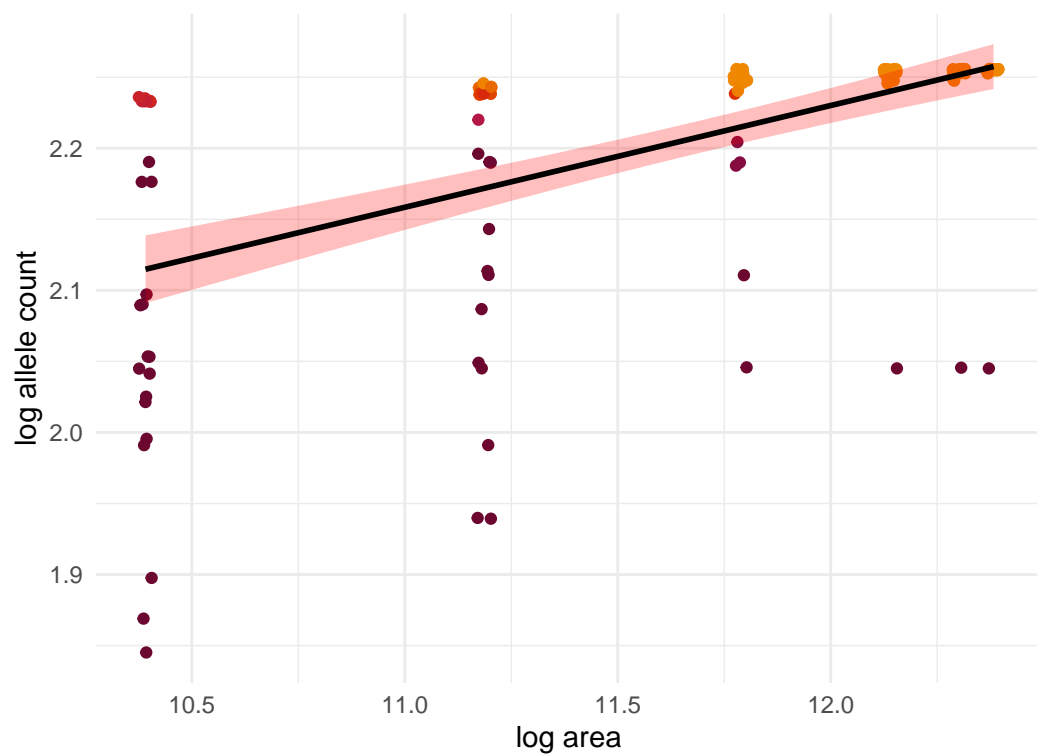
Hydromantes platycephalus; $z=0.275$



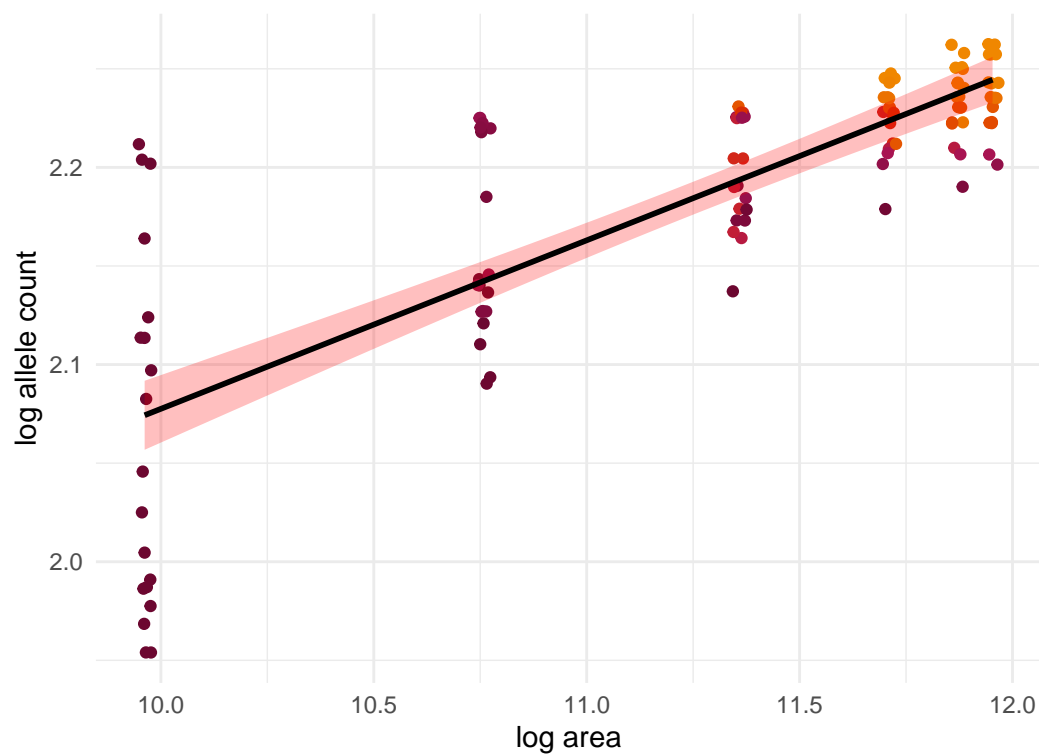
Rangifer tarandus; $z=0.111$



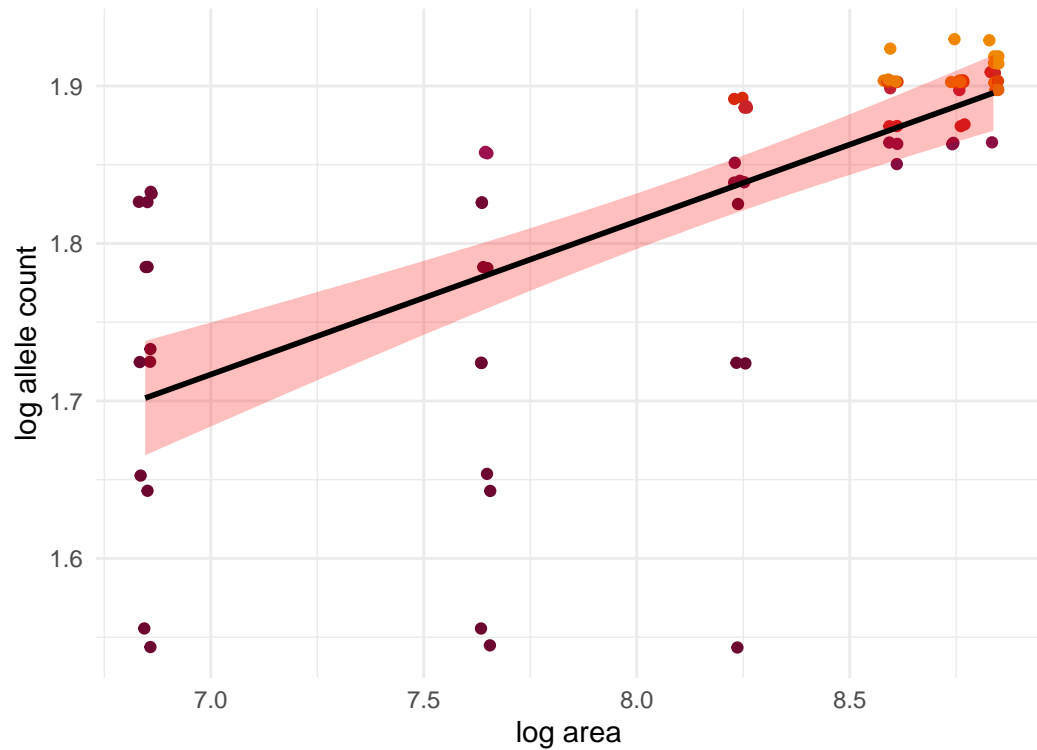
Rhinolophus ferrumequinum; $z=0.072$



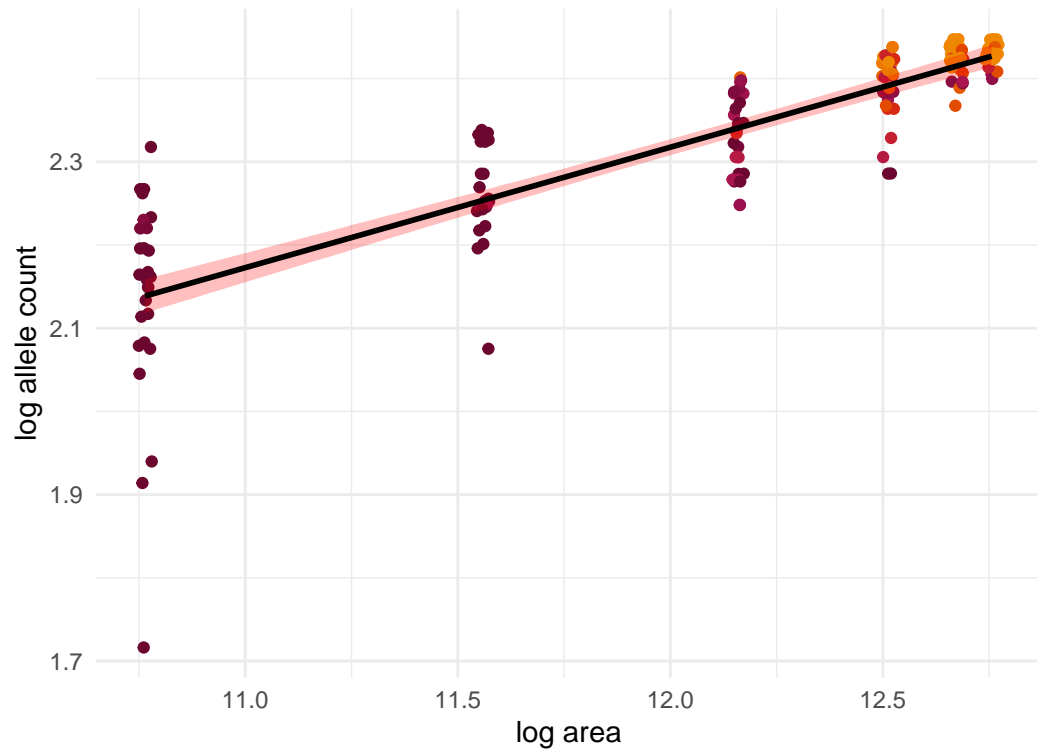
Dipsosaurus dorsalis; $z=0.085$



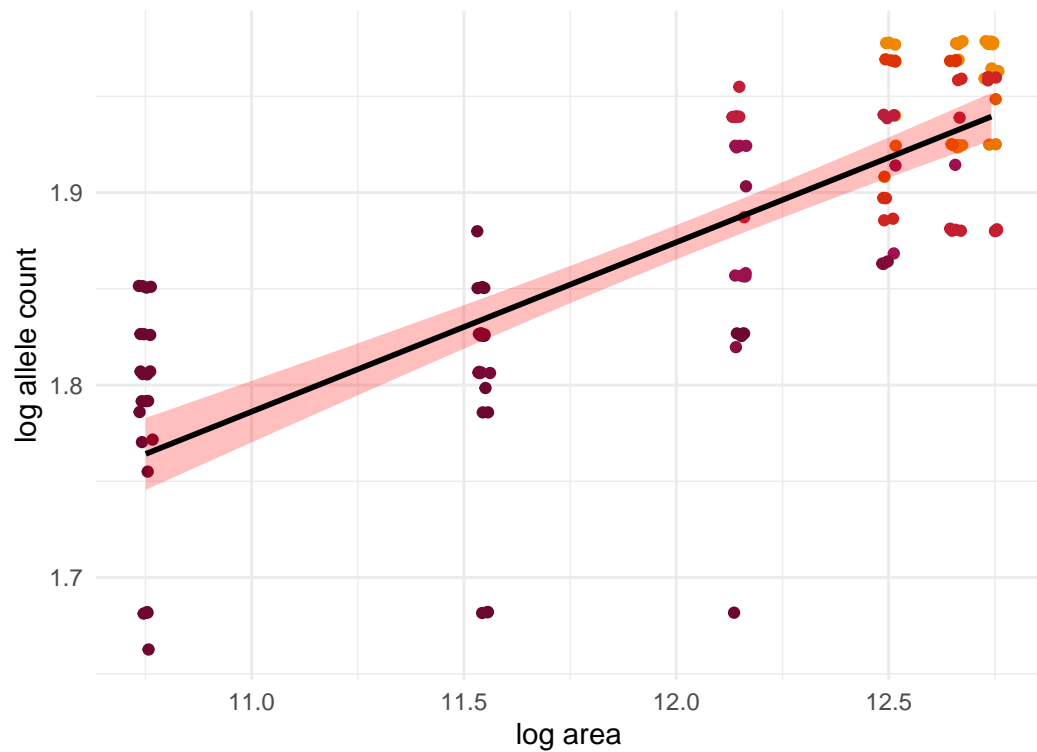
Uma inornata; $z=0.097$



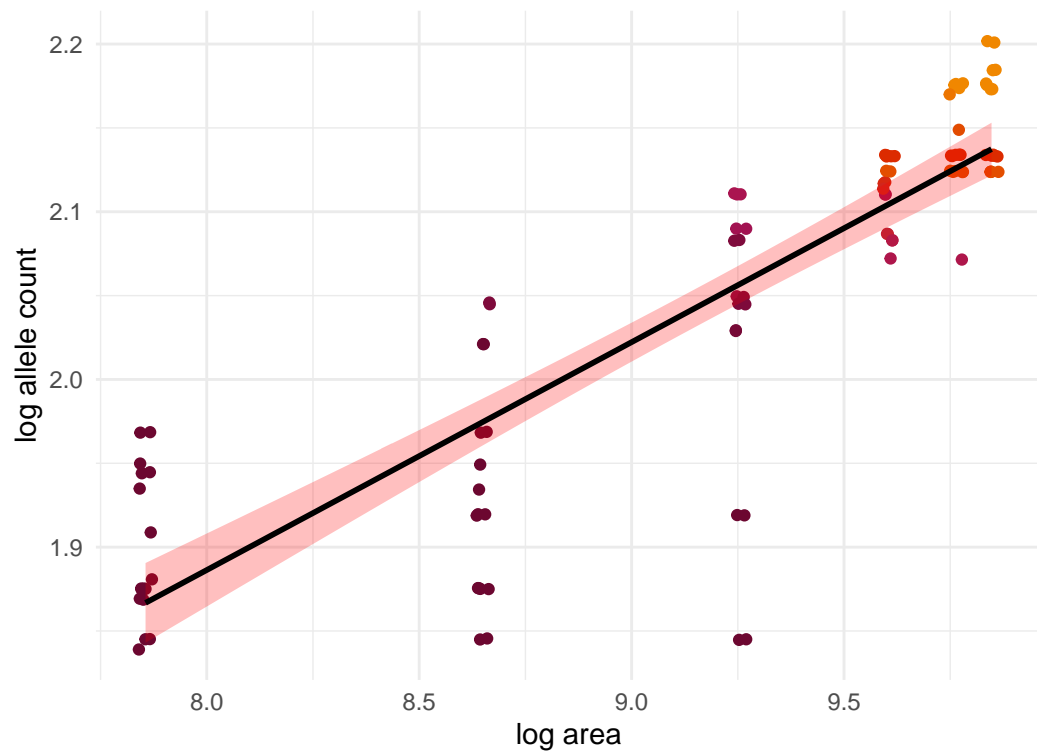
Rangifer tarandus; $z=0.145$



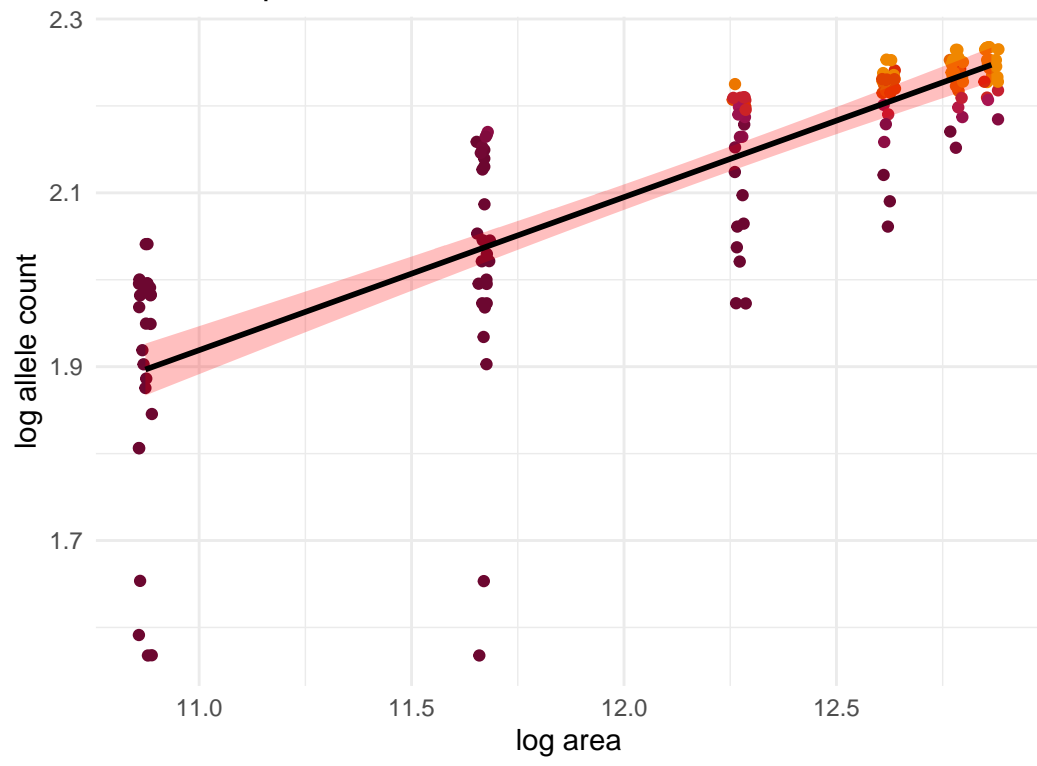
Miniopterus schreibersii; $z=0.088$



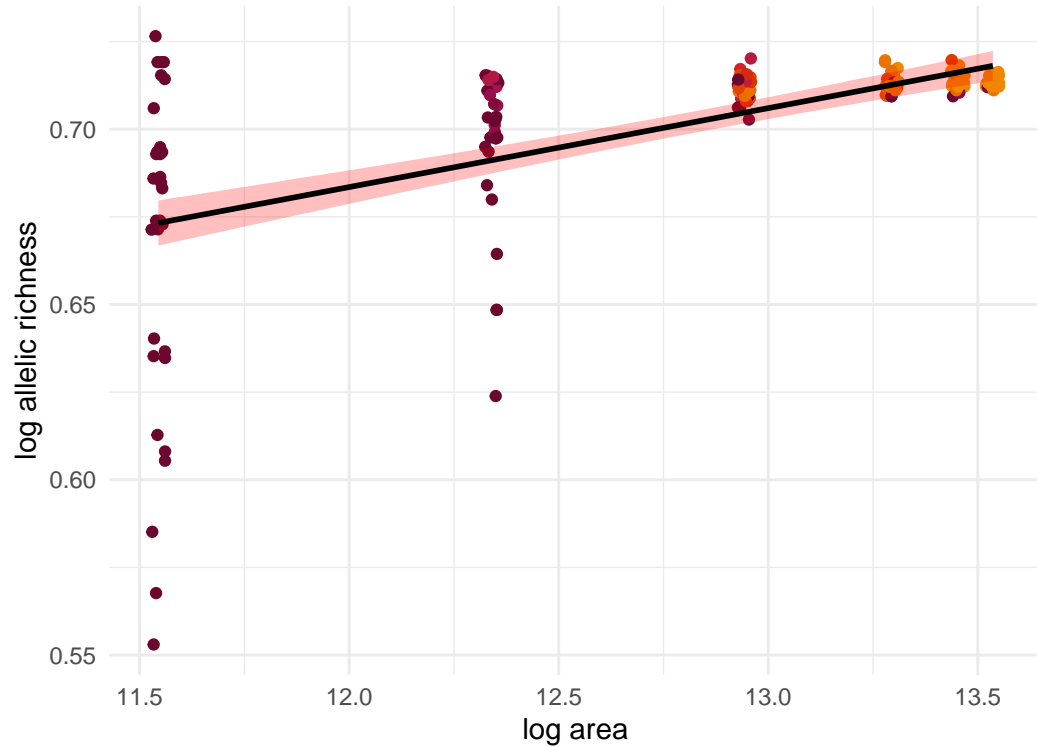
Sorex antinorii; $z=0.136$



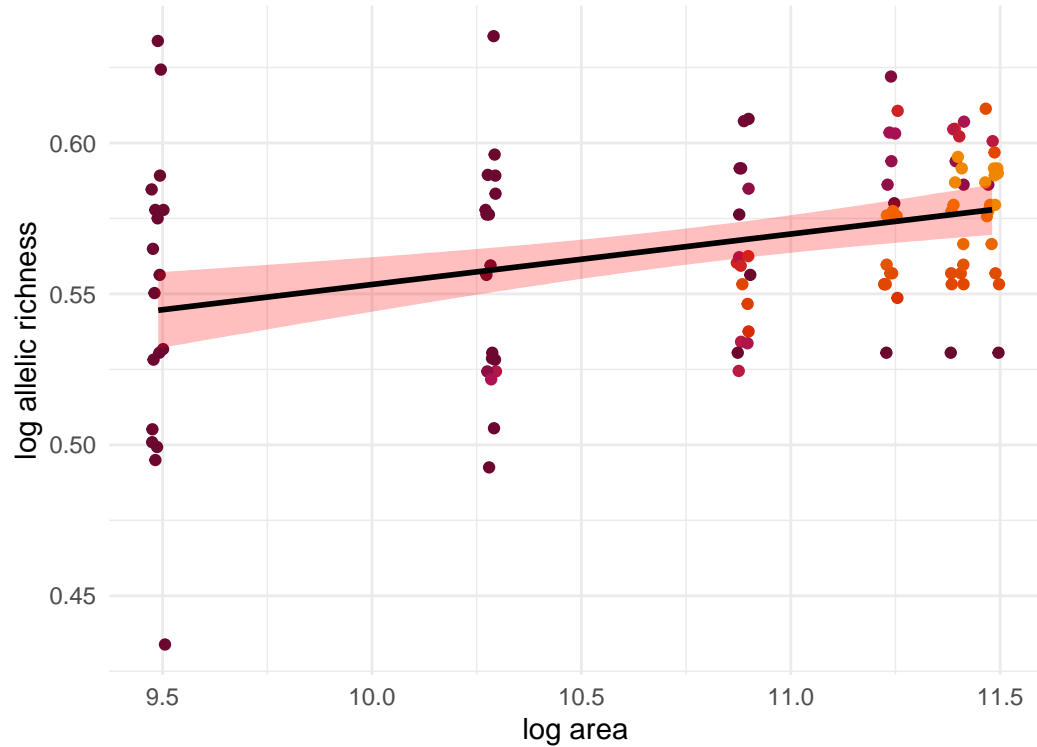
Cervus elaphus; z=0.176



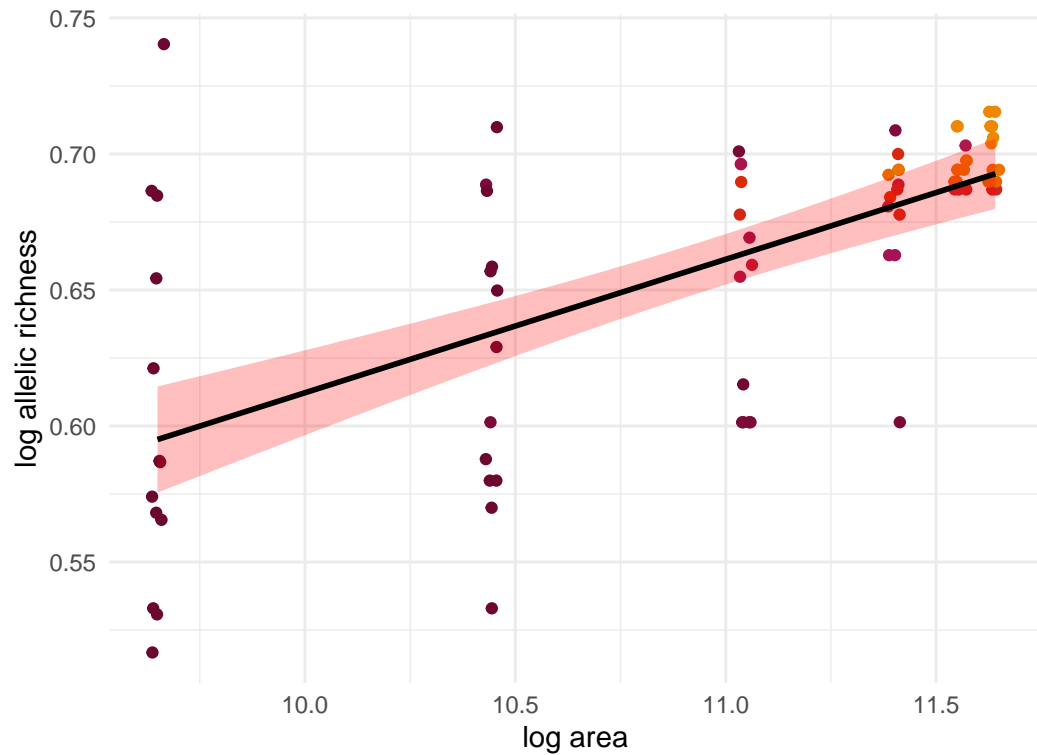
Poecile atricapillus; $z=0.023$



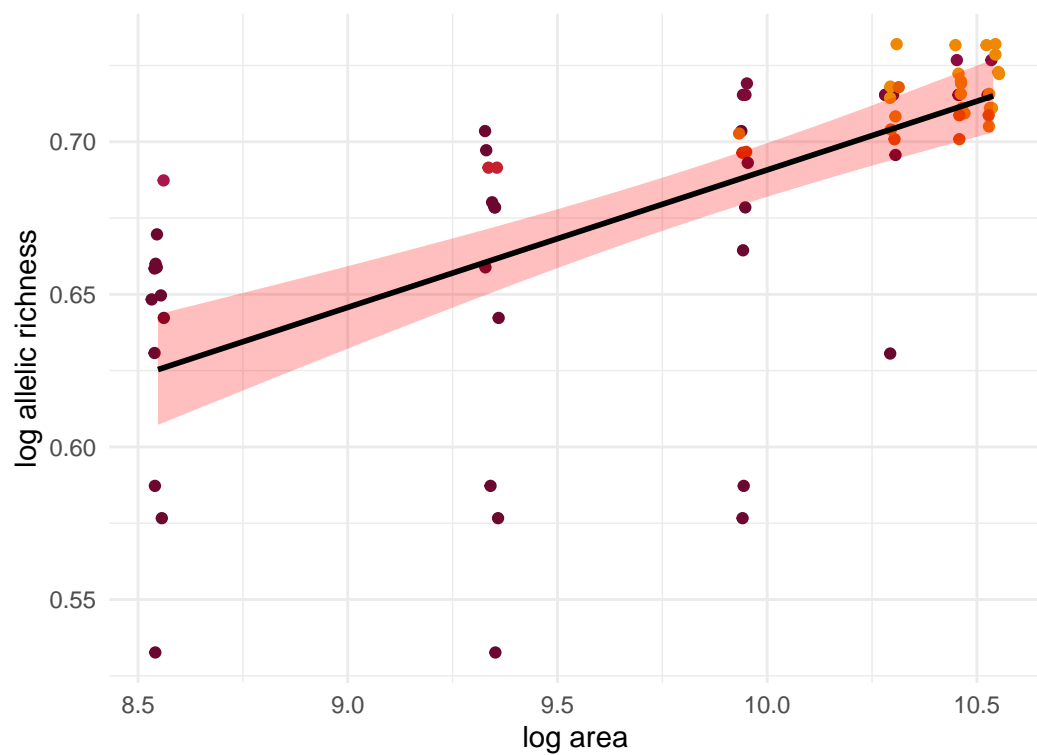
Sus scrofa; $z=0.017$



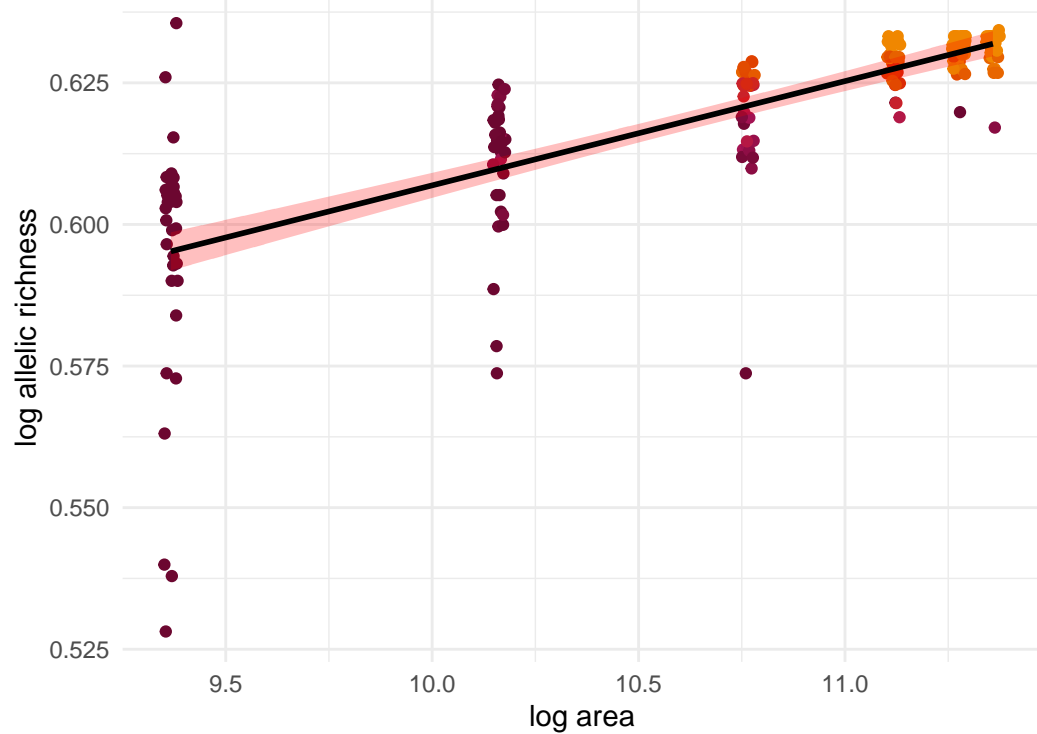
Capreolus capreolus; $z=0.049$



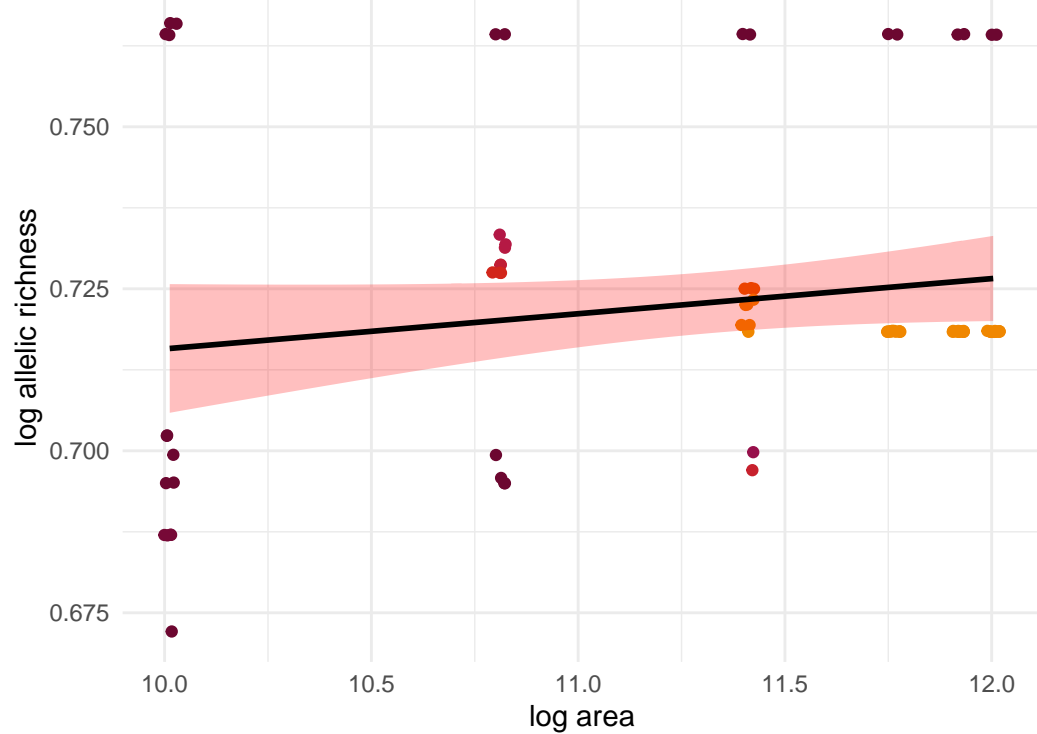
Campylorhynchus brunneicapillus; $z=0.045$



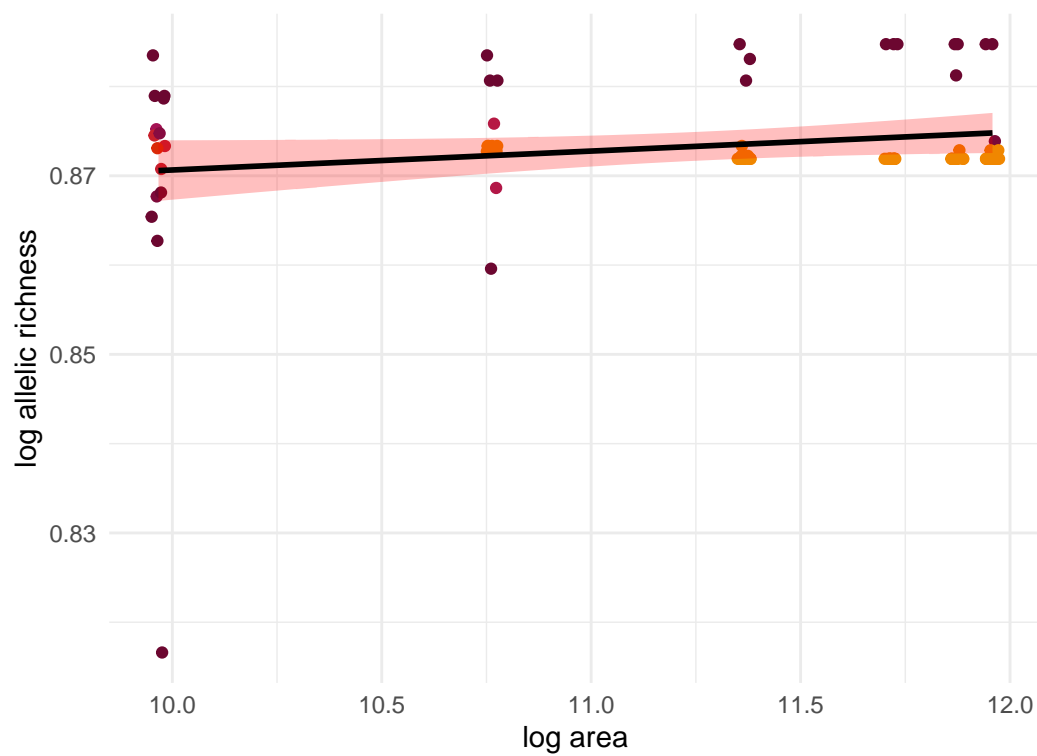
Pekania pennanti; z=0.018



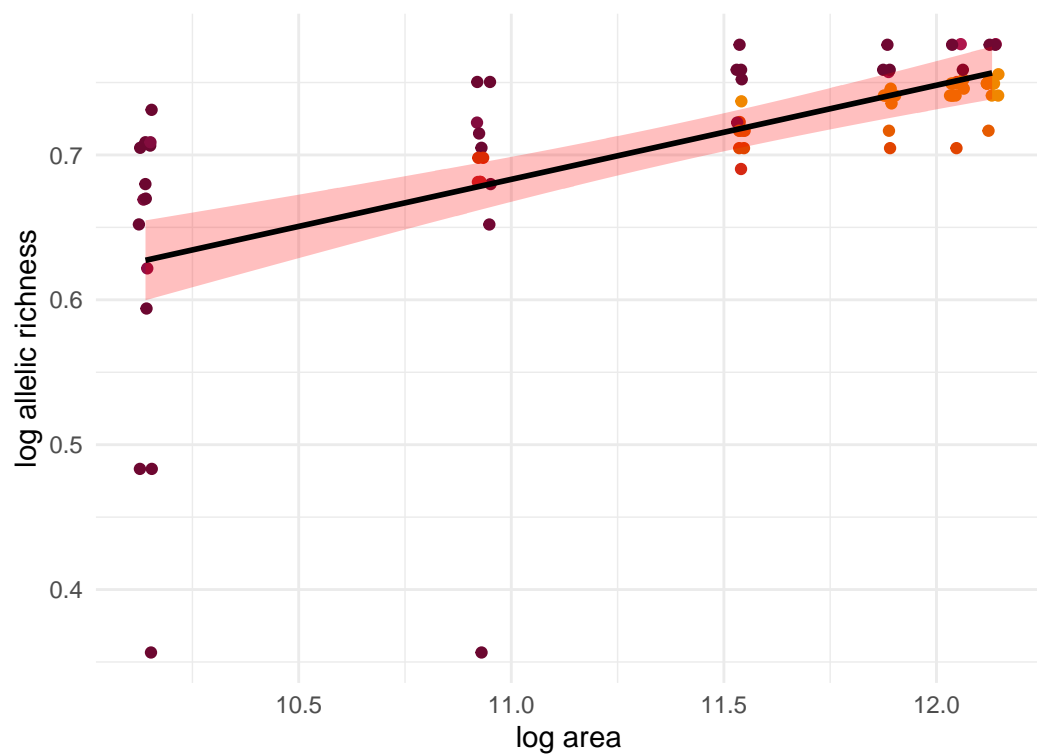
Nyctalus leisleri; z=NA



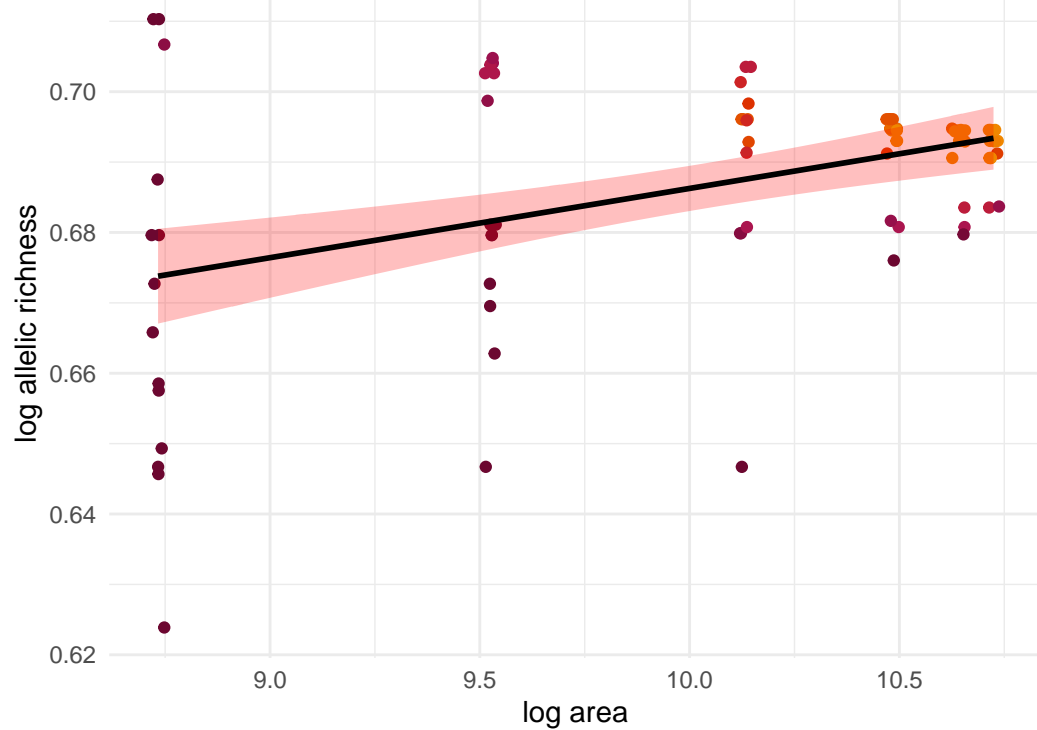
Myotis lucifugus; z=NA



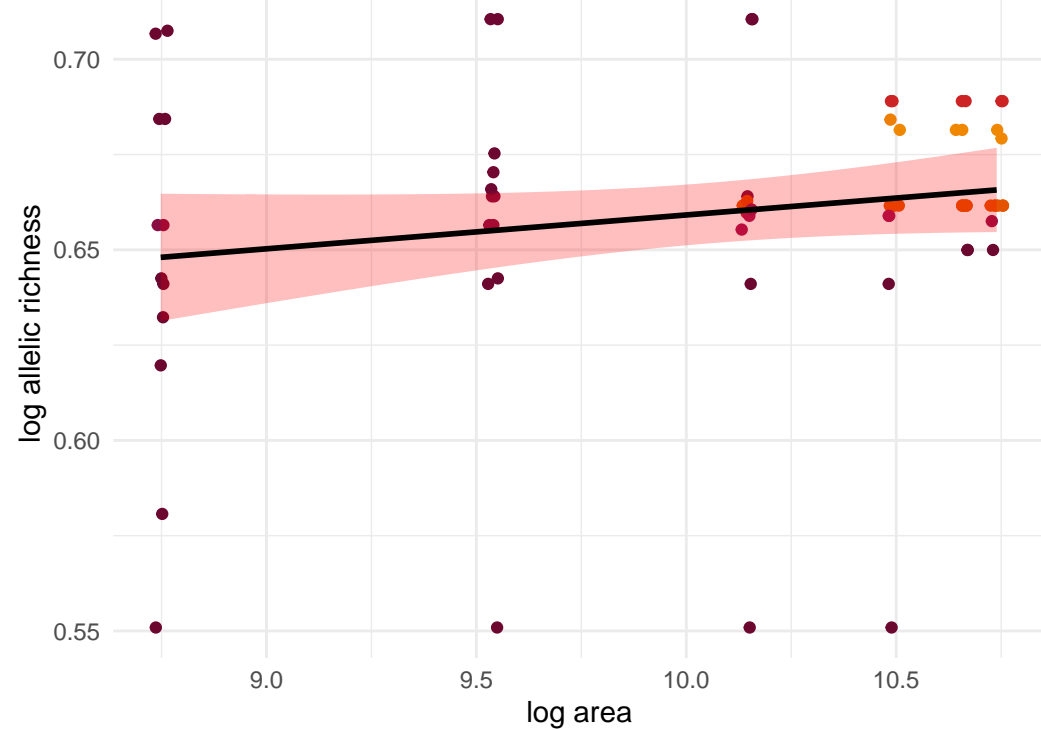
Vicugna vicugna; z=0.065



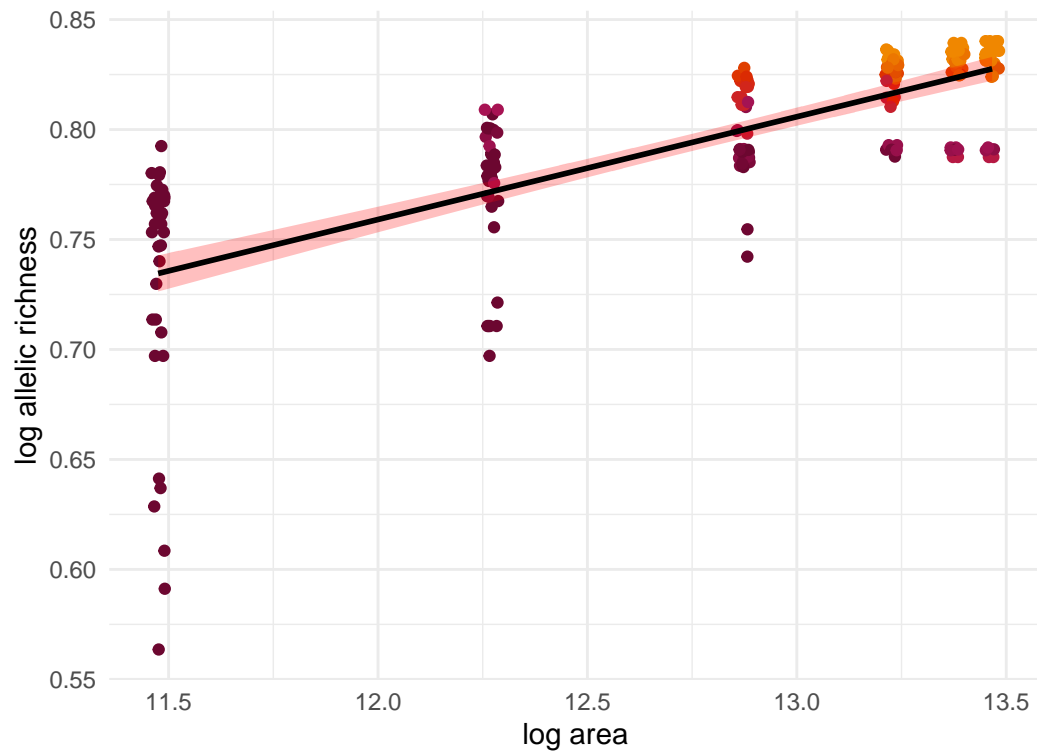
Tamiasciurus douglasii; $z=0.01$



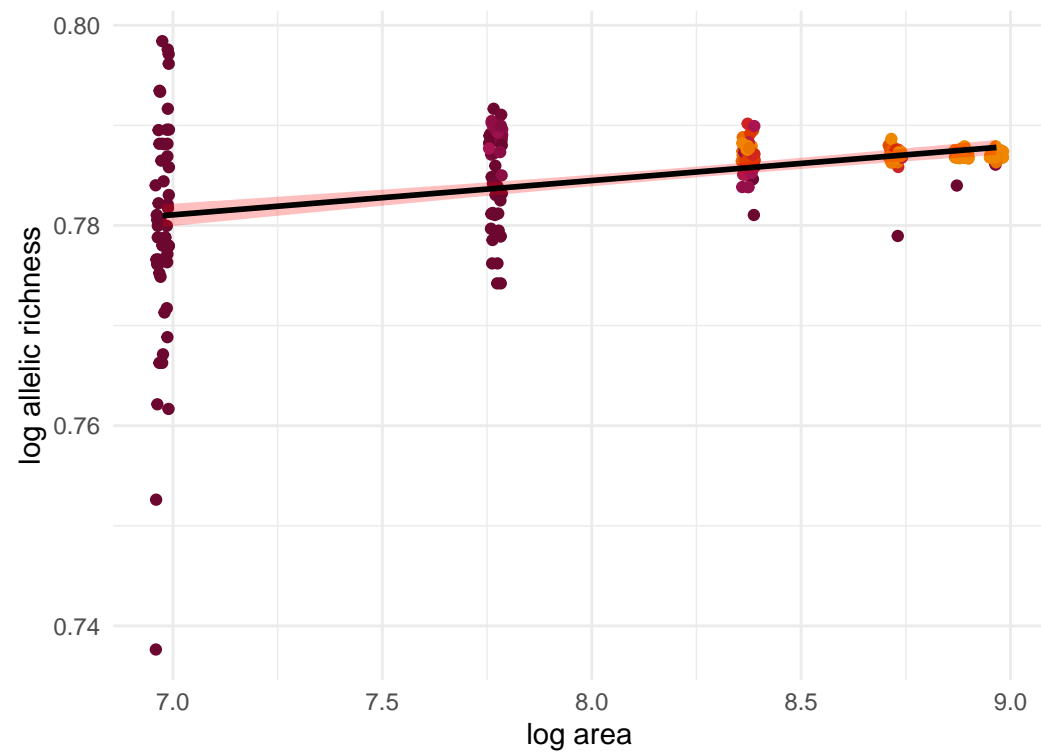
Tamiasciurus hudsonicus; $z=NA$



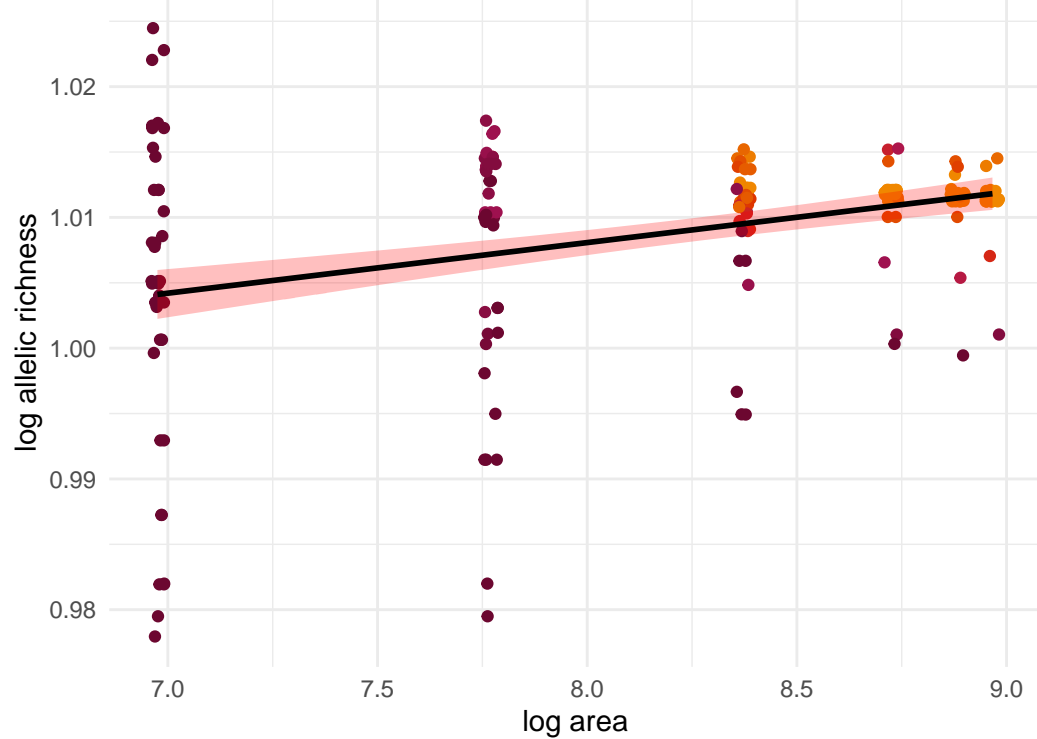
Lepus americanus; $z=0.047$



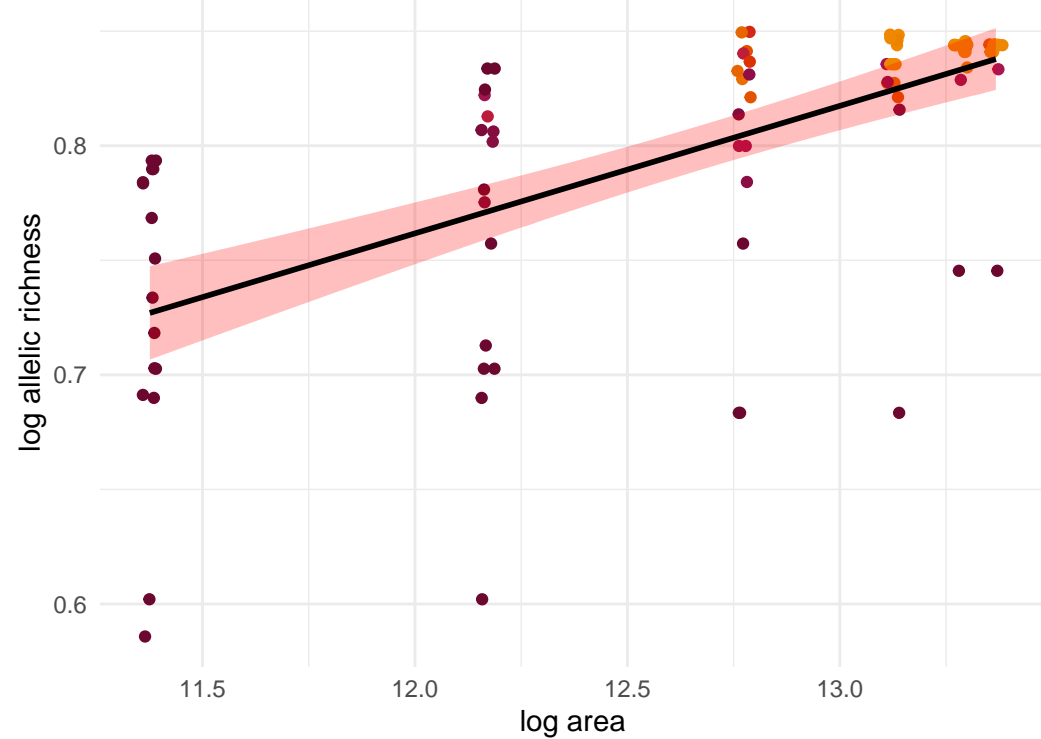
Ambystoma maculatum; $z=0.003$



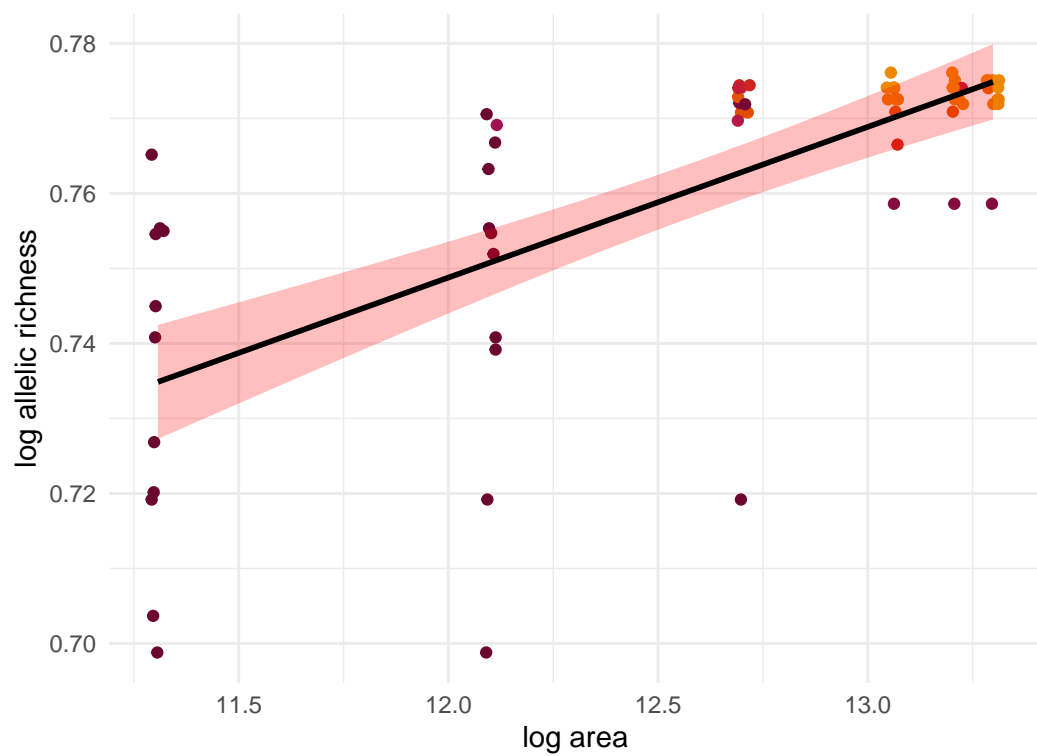
Lithobates sylvaticus; $z=0.004$



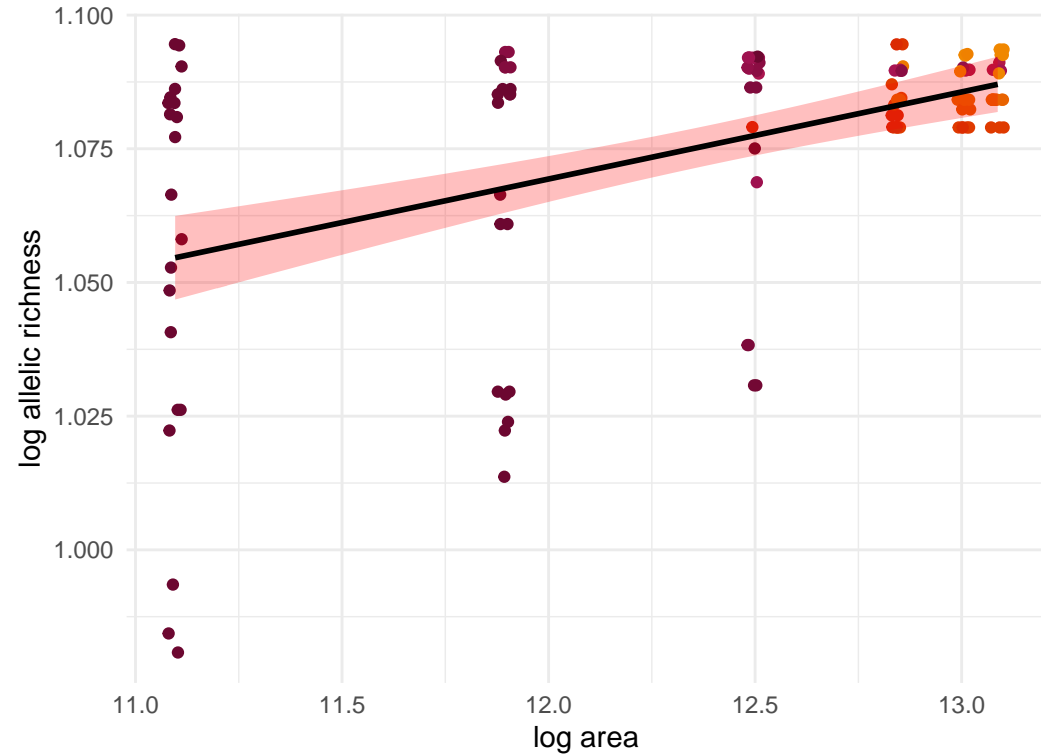
Ursus arctos; $z=0.056$



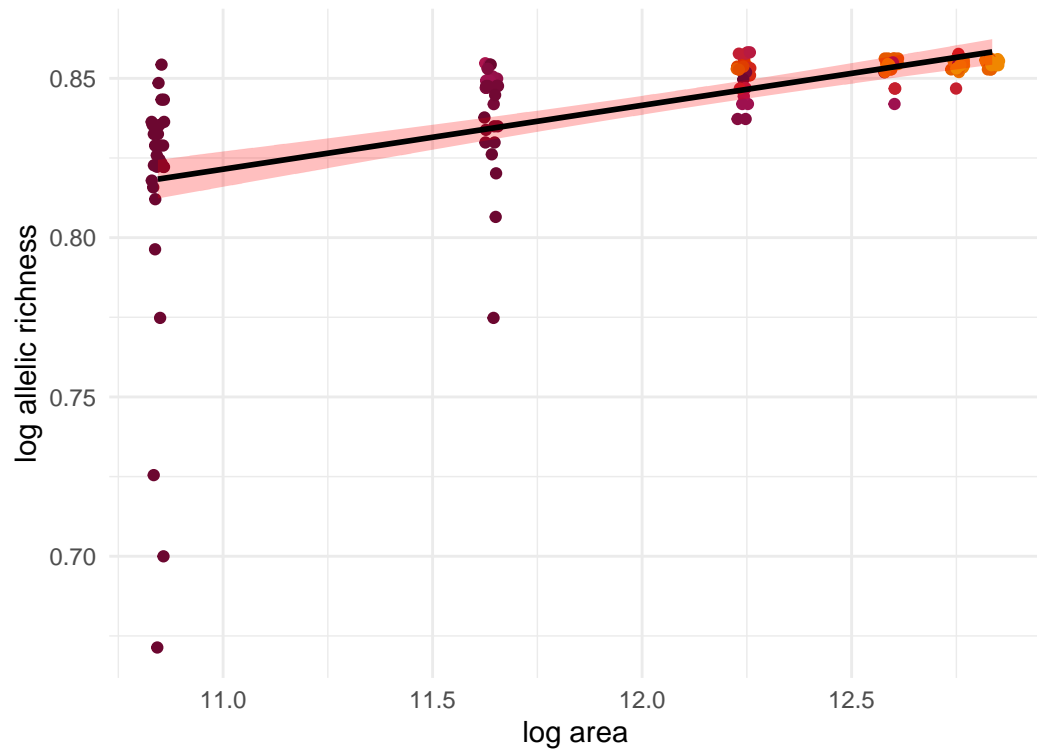
Ursus maritimus; $z=0.02$



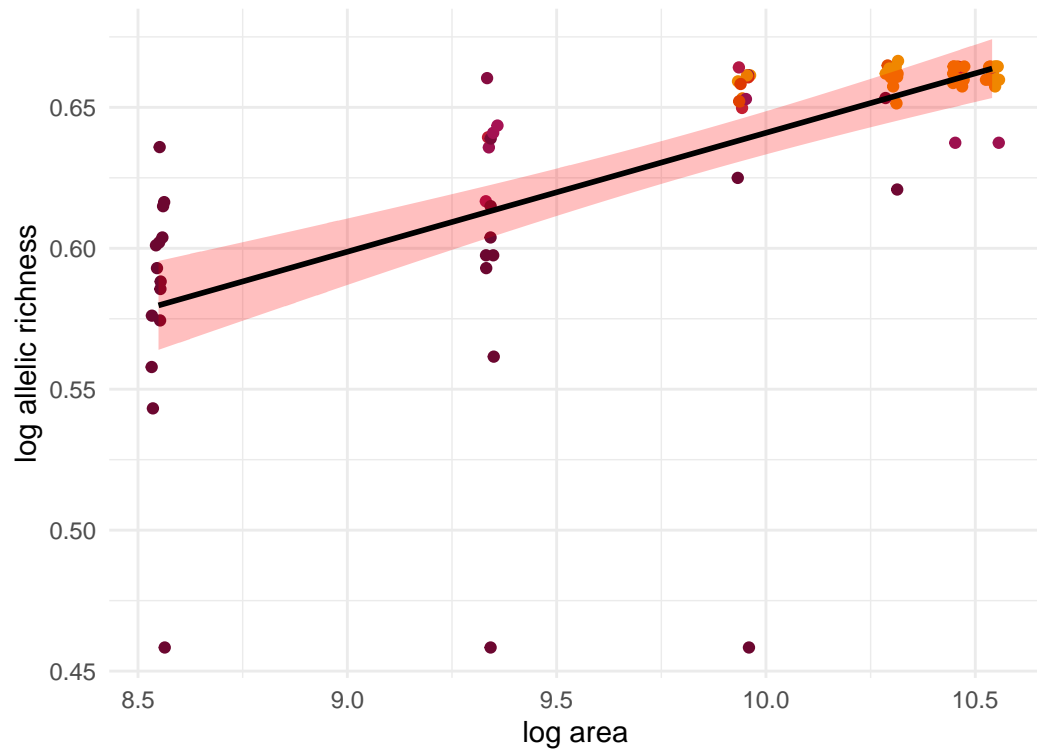
Myotis lucifugus; $z=0.016$



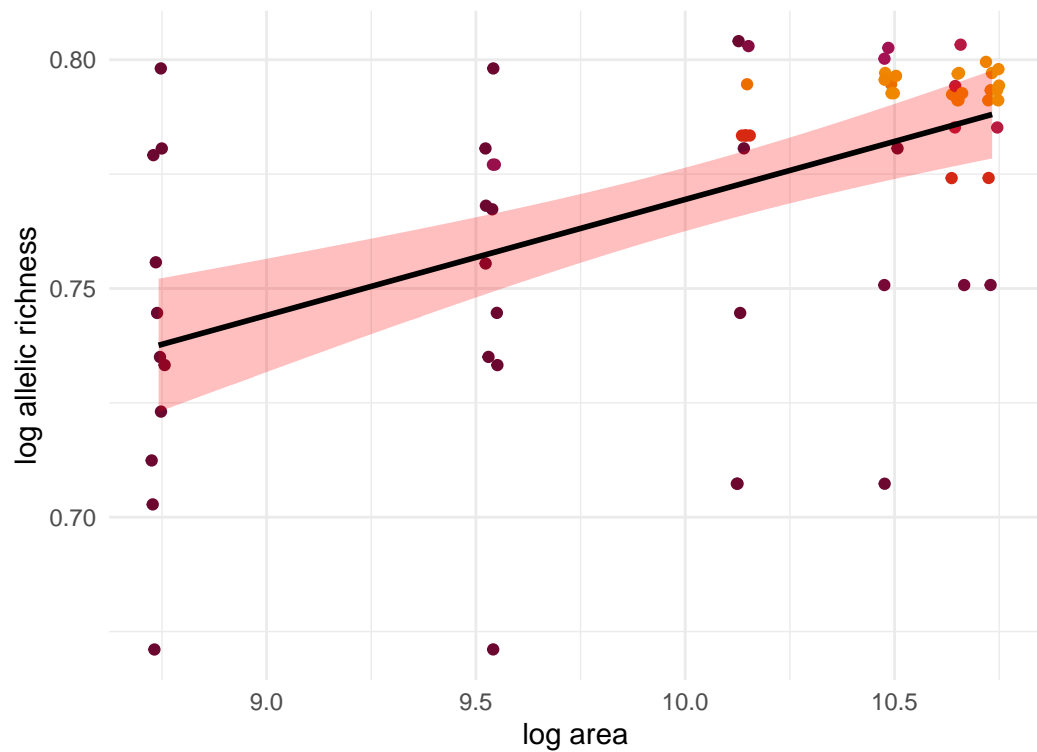
Lithobates sylvaticus; $z=0.02$



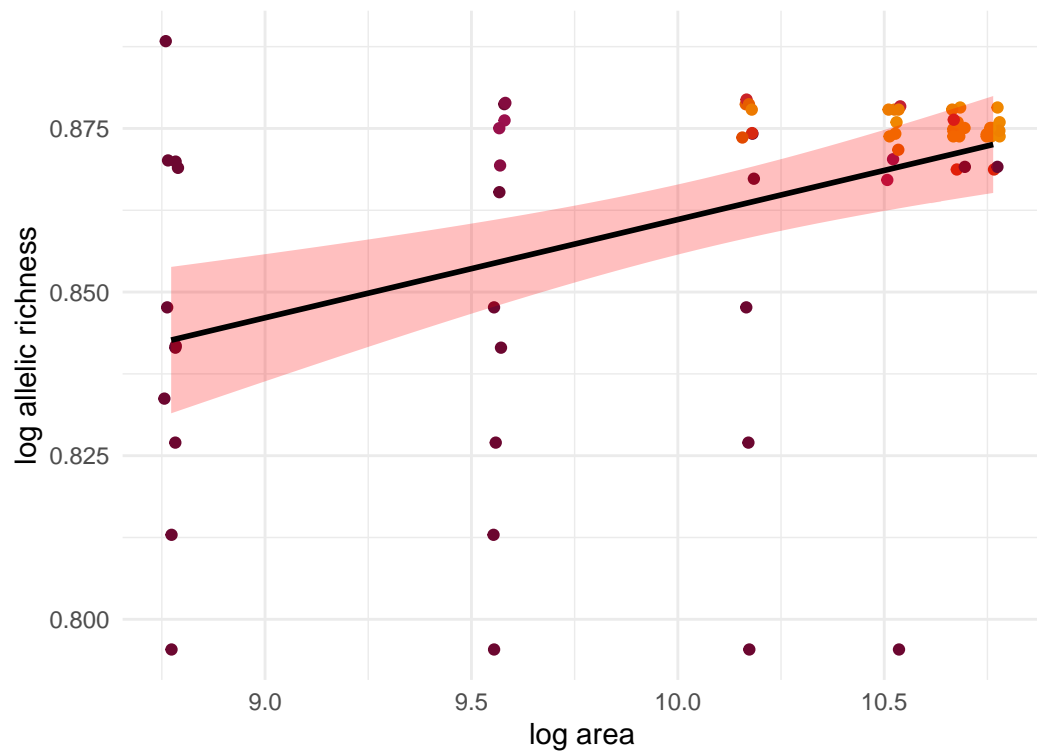
Ovis canadensis; $z=0.042$



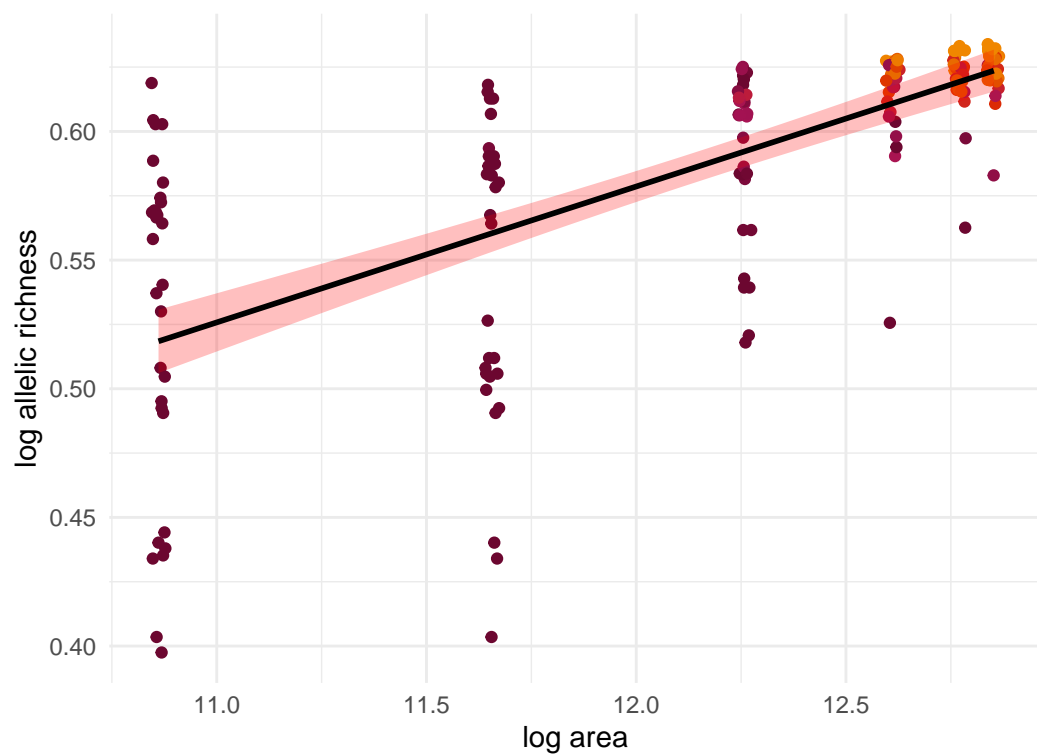
Geospiza fortis; $z=0.025$



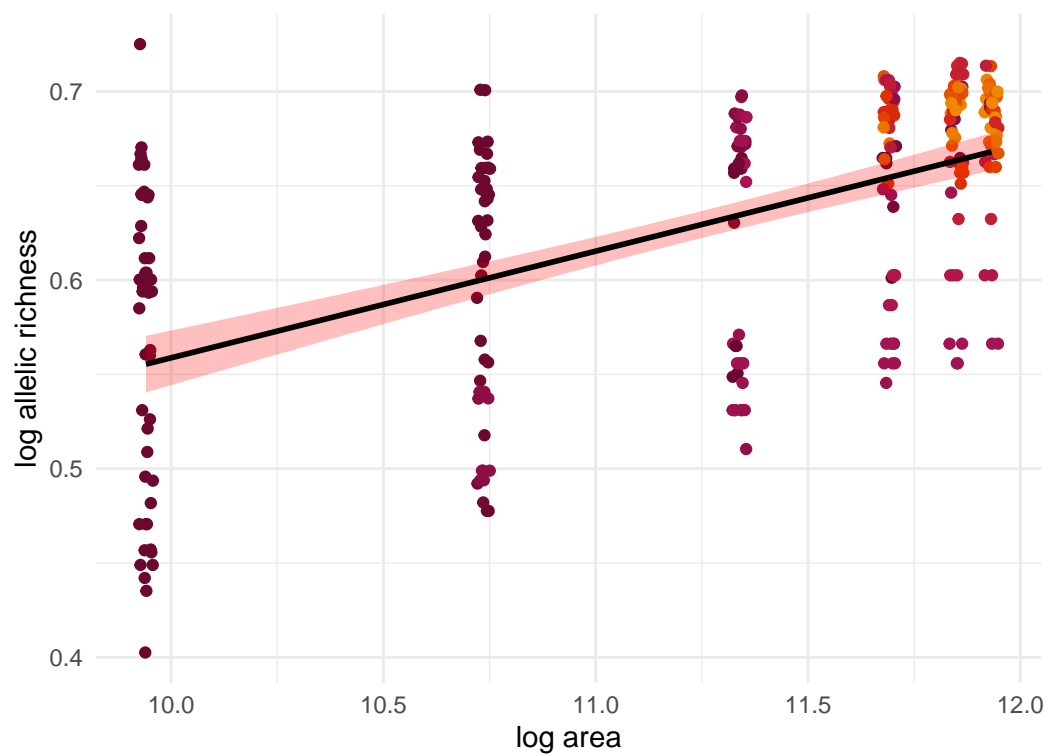
Geospiza fuliginosa; $z=0.015$



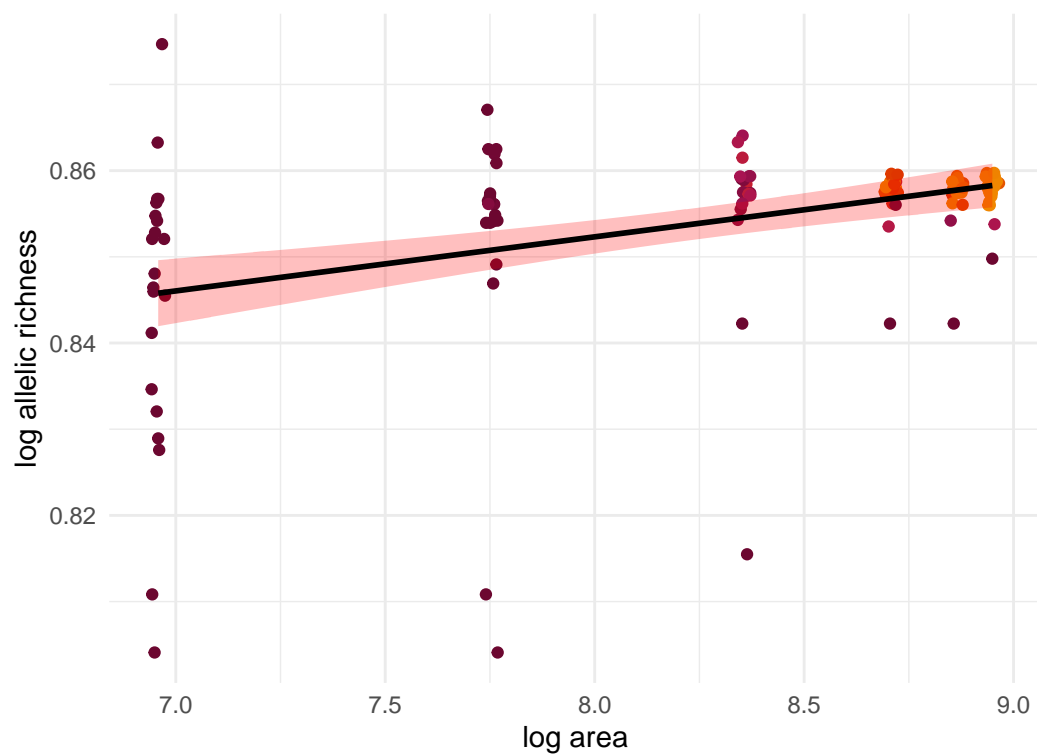
Meles meles; $z=0.053$



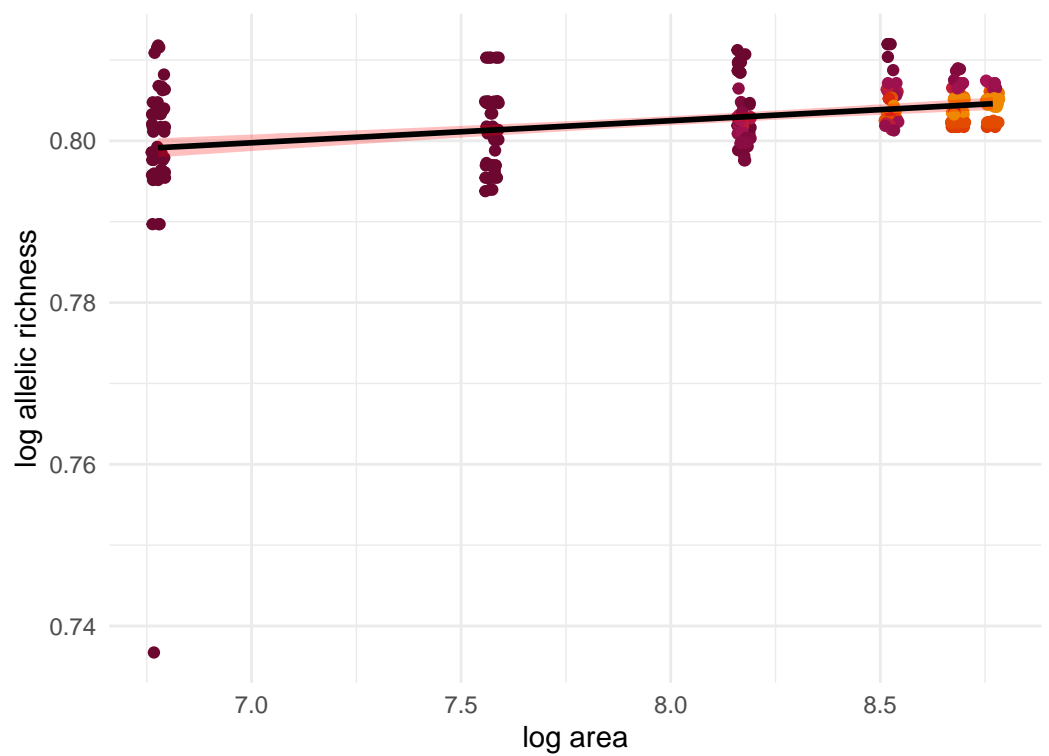
Gopherus polyphemus; $z=0.057$



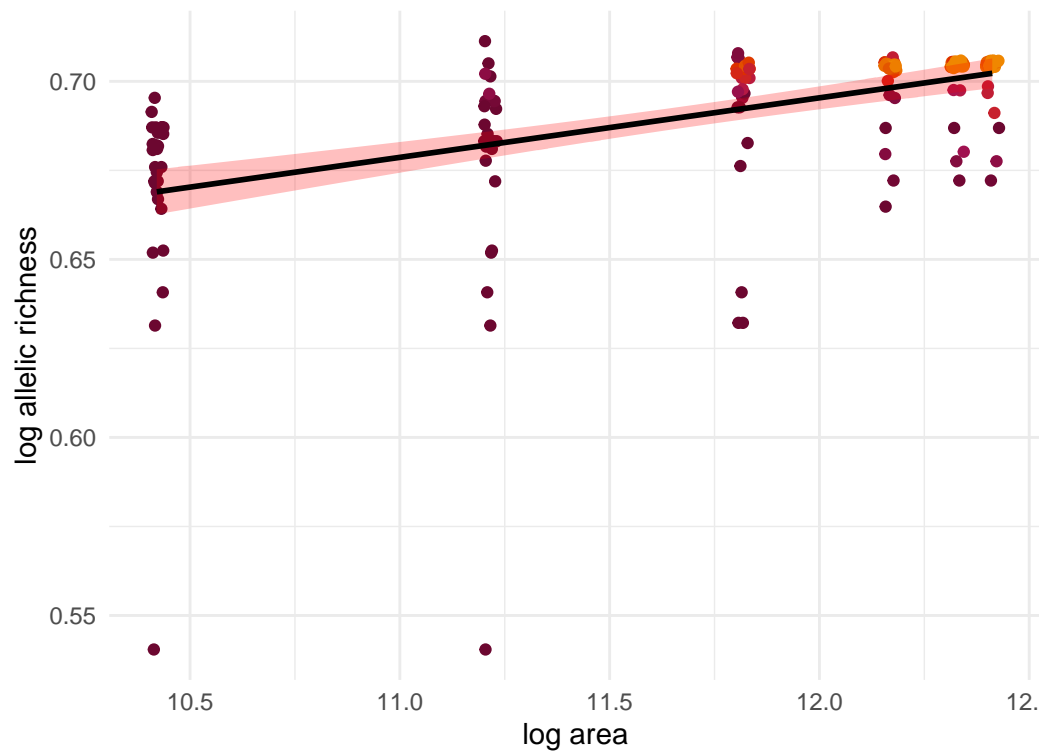
Geospiza fuliginosa; $z=0.006$



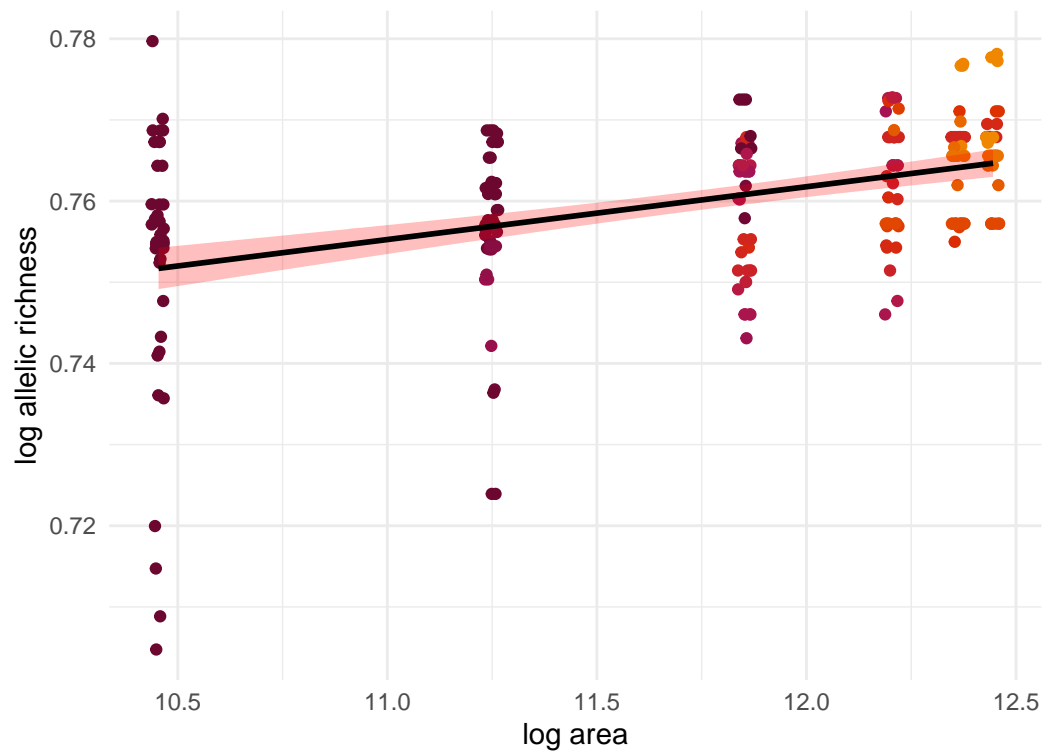
Microtus arvalis; $z=0.003$



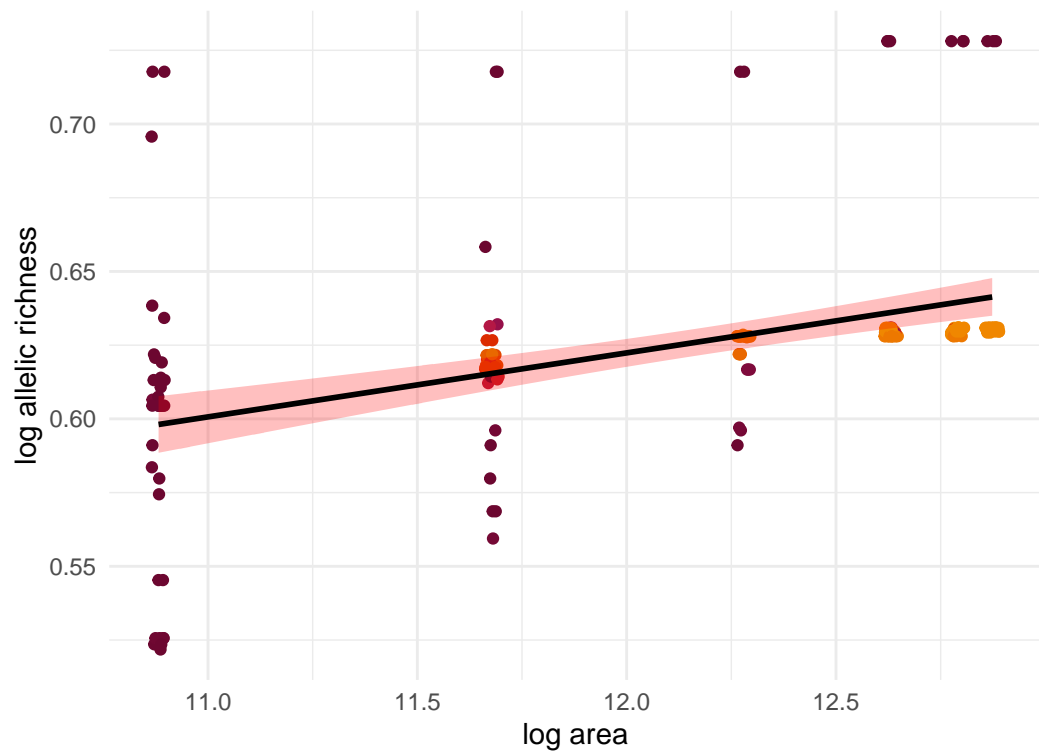
Aphelocoma californica; $z=0.017$



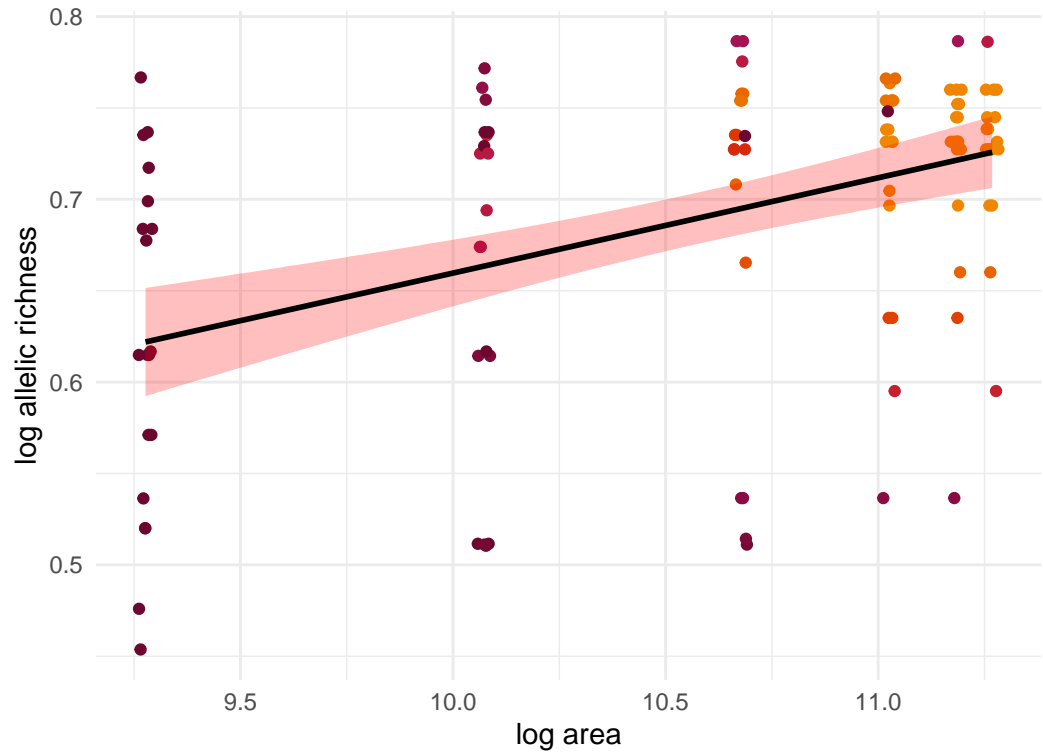
Canis latrans; $z=0.007$



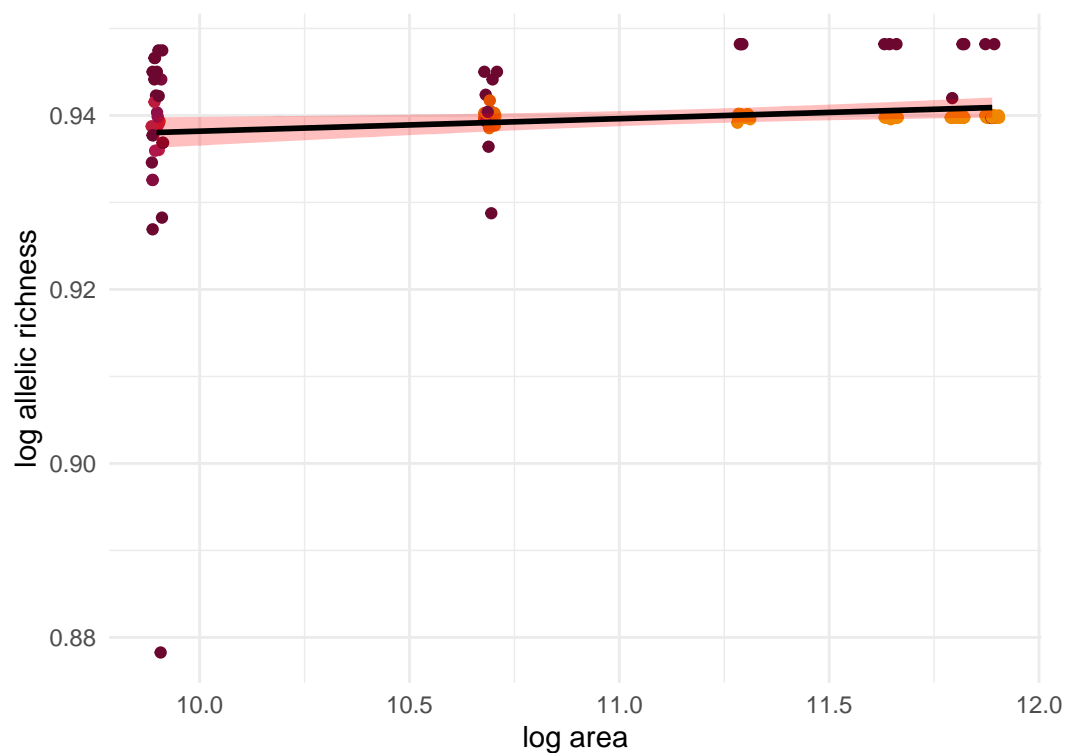
Rousettus aegyptiacus; $z=0.022$



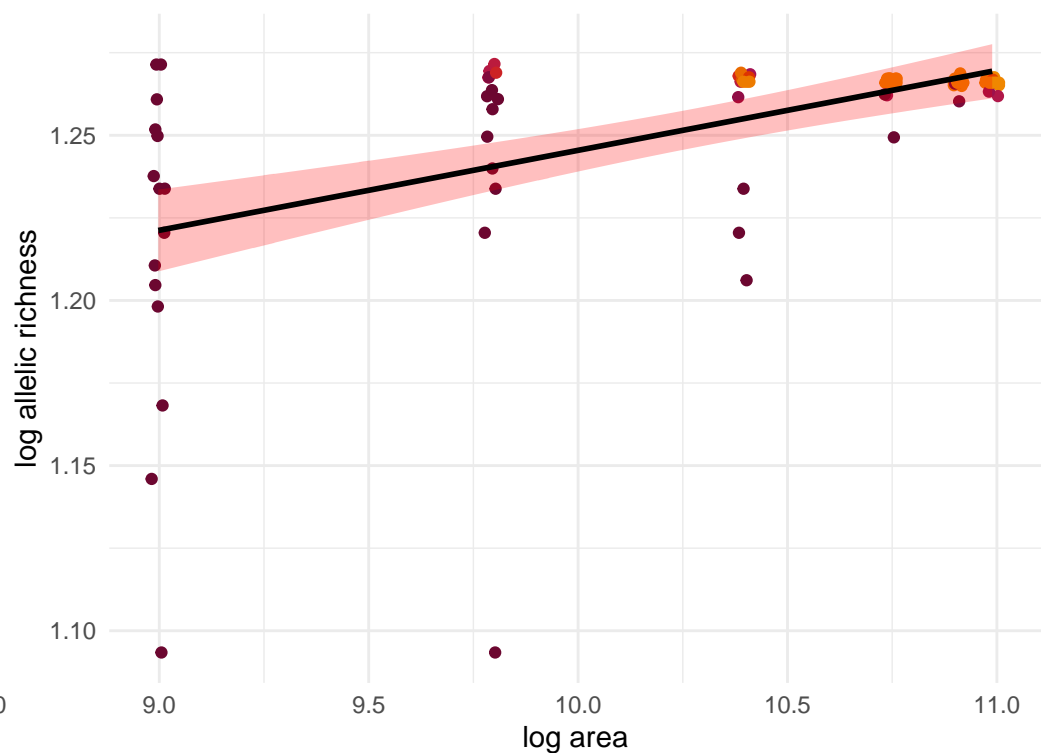
Ambystoma maculatum; $z=0.052$



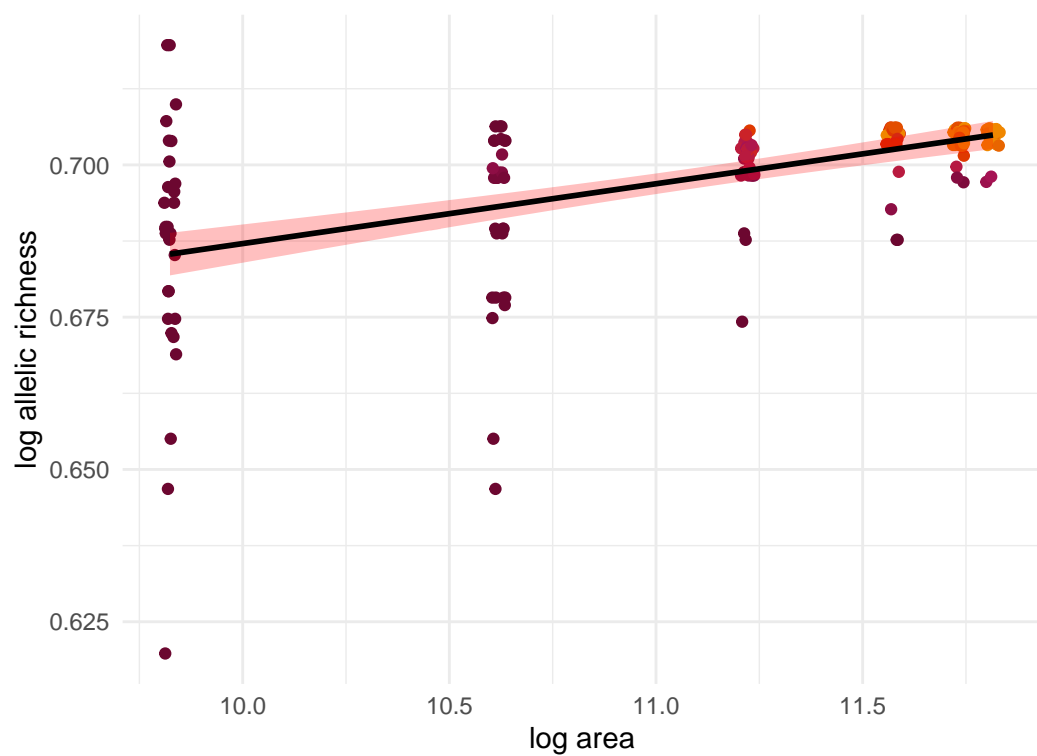
Myotis lucifugus; $z=0.001$



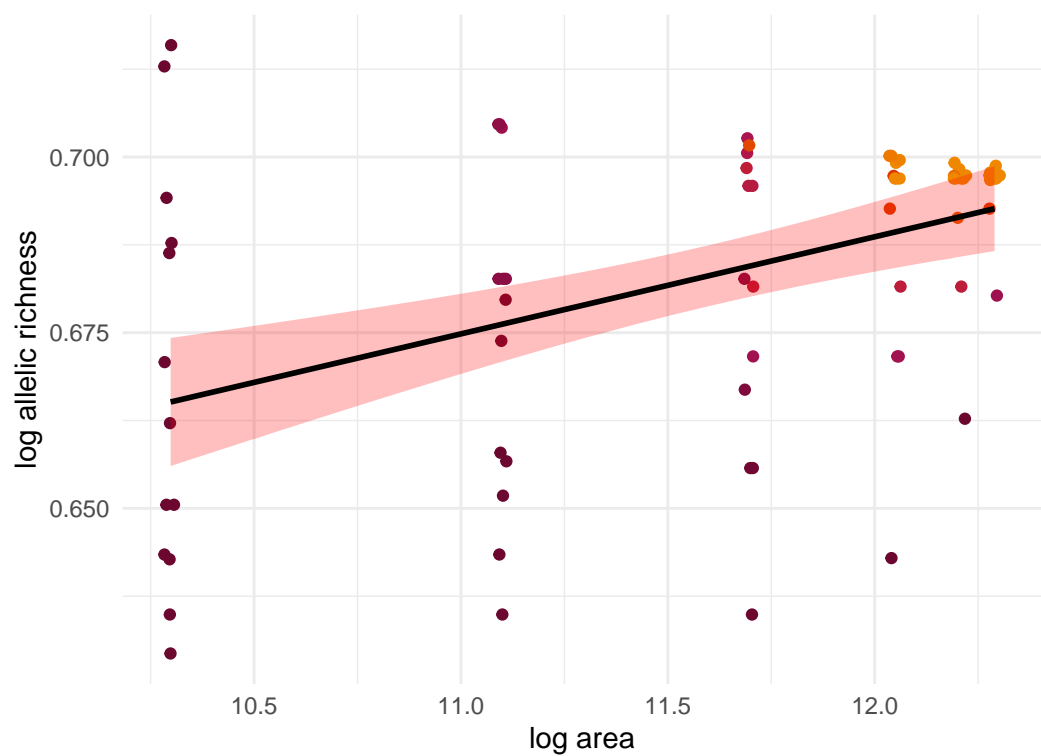
Myotis septentrionalis; $z=0.024$



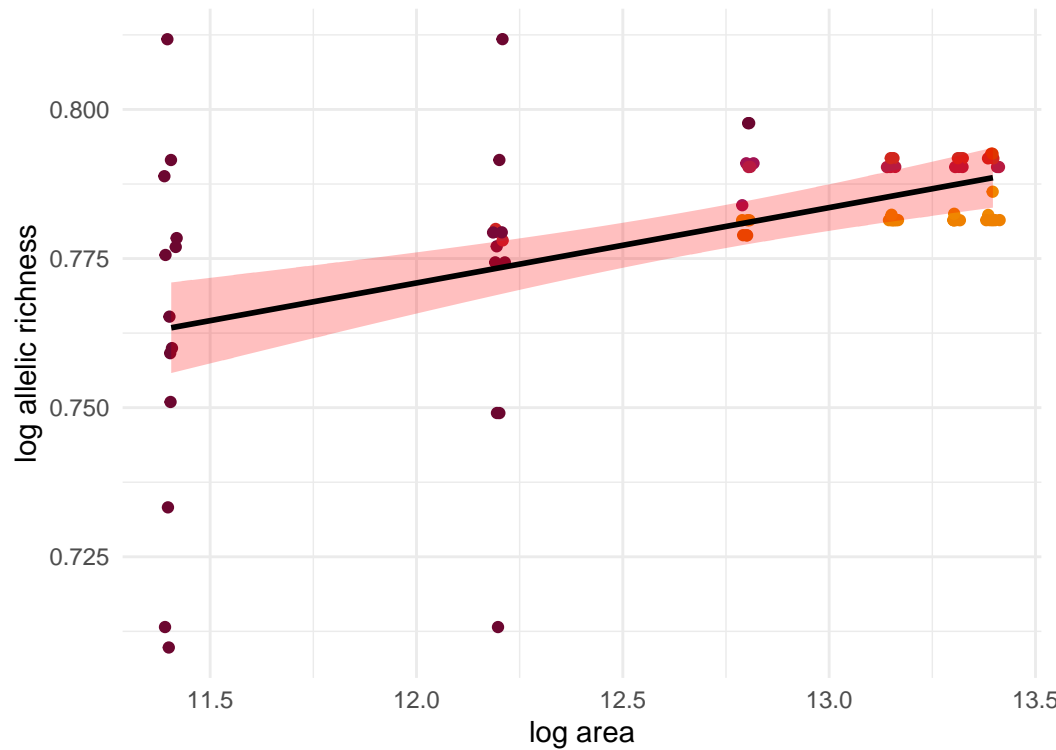
Martes americana; $z=0.01$



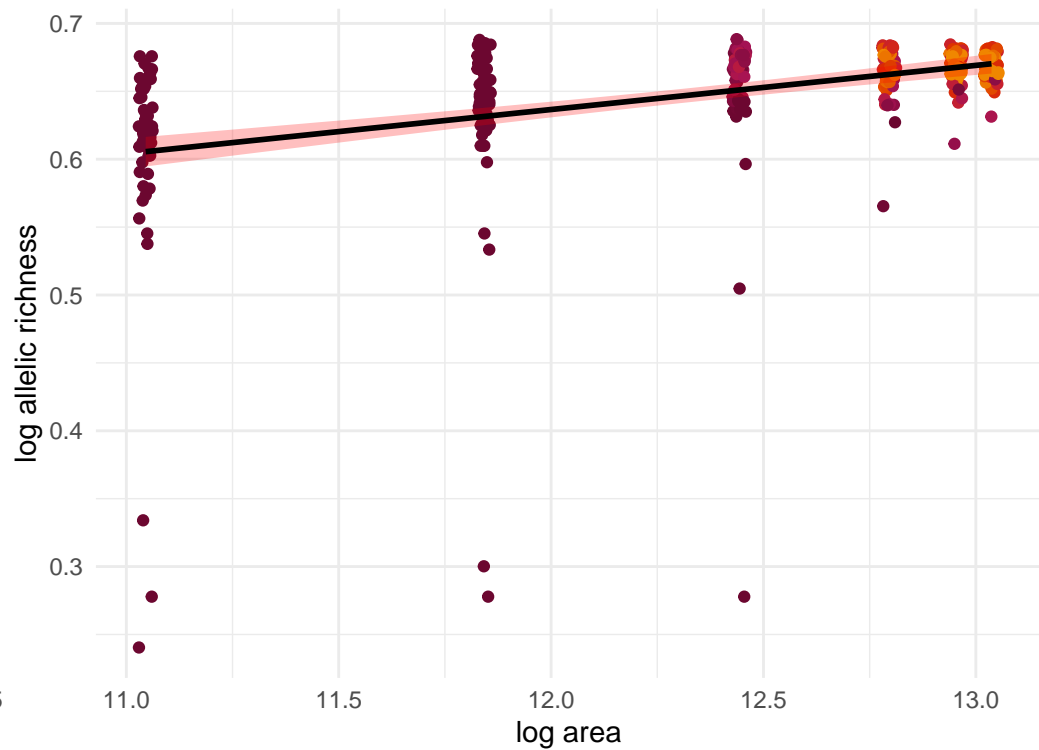
Lemmus lemmus; $z=0.014$



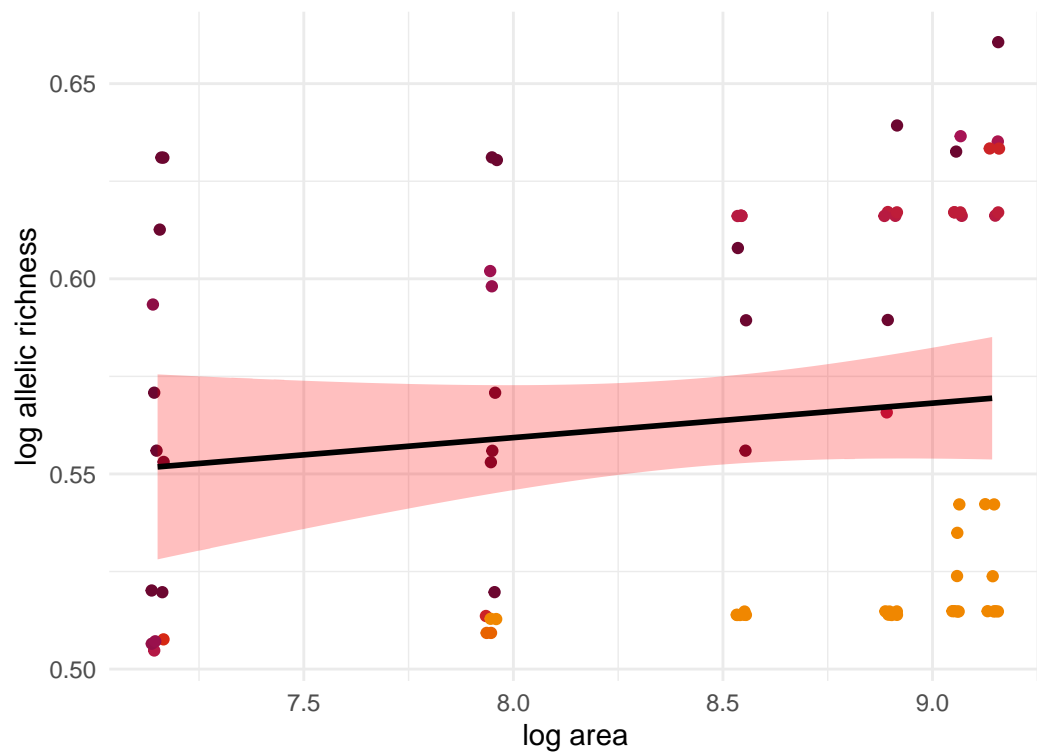
Poecile hudsonicus; $z=0.013$



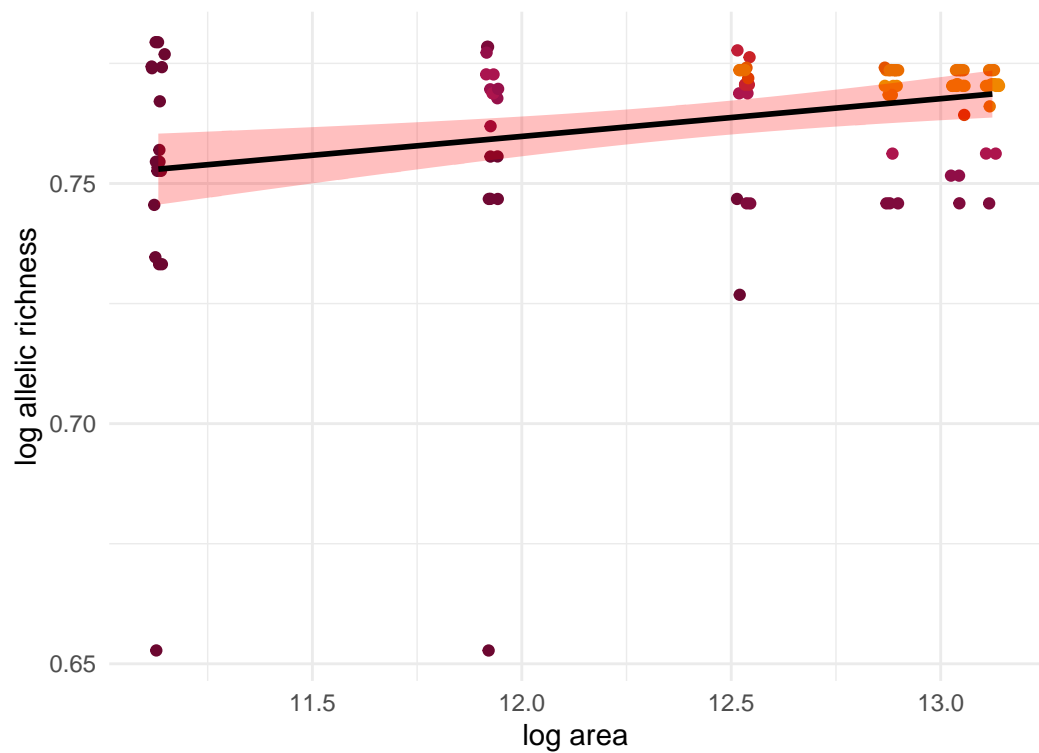
Odocoileus hemionus; $z=0.033$



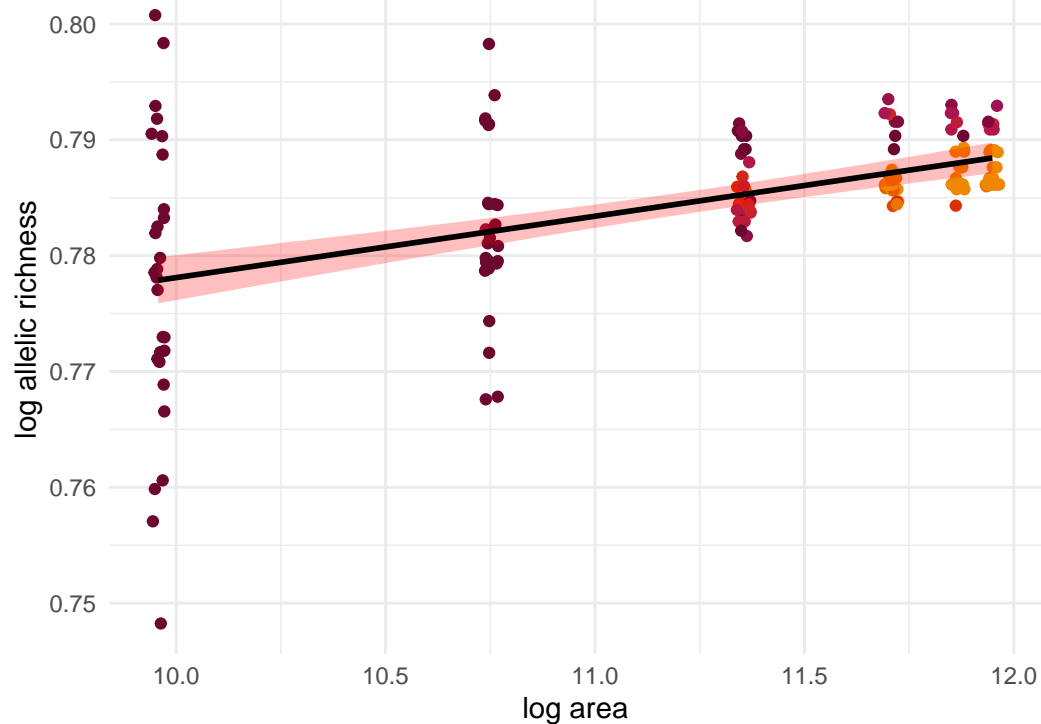
Amblyrhynchus cristatus; $z=NA$



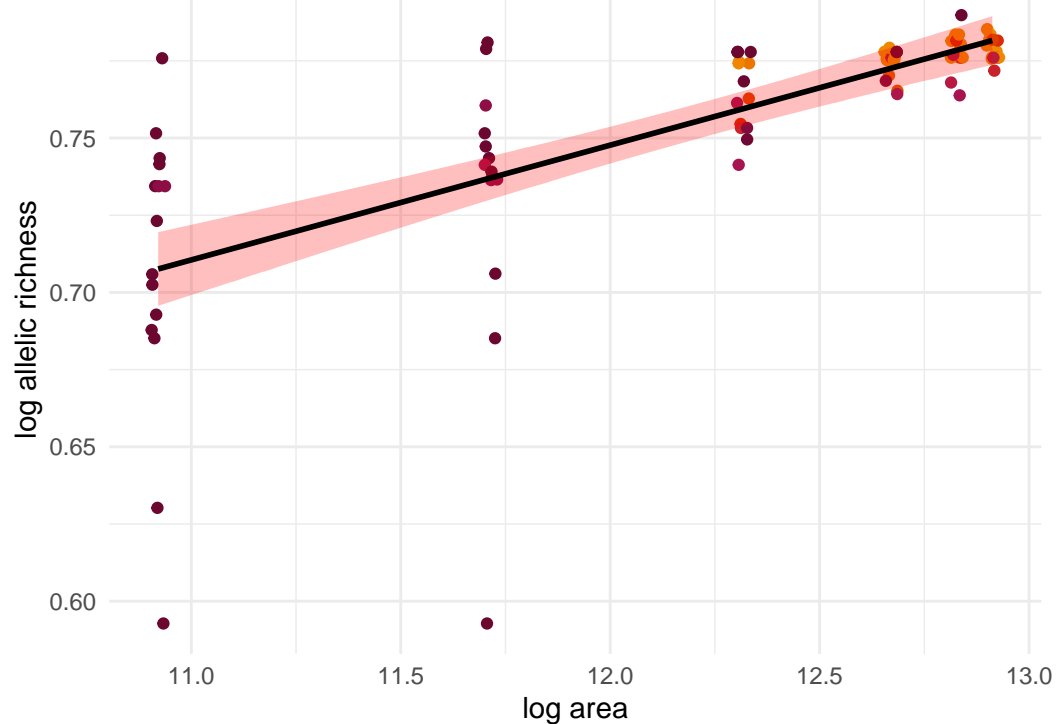
Rangifer tarandus; $z=0.008$



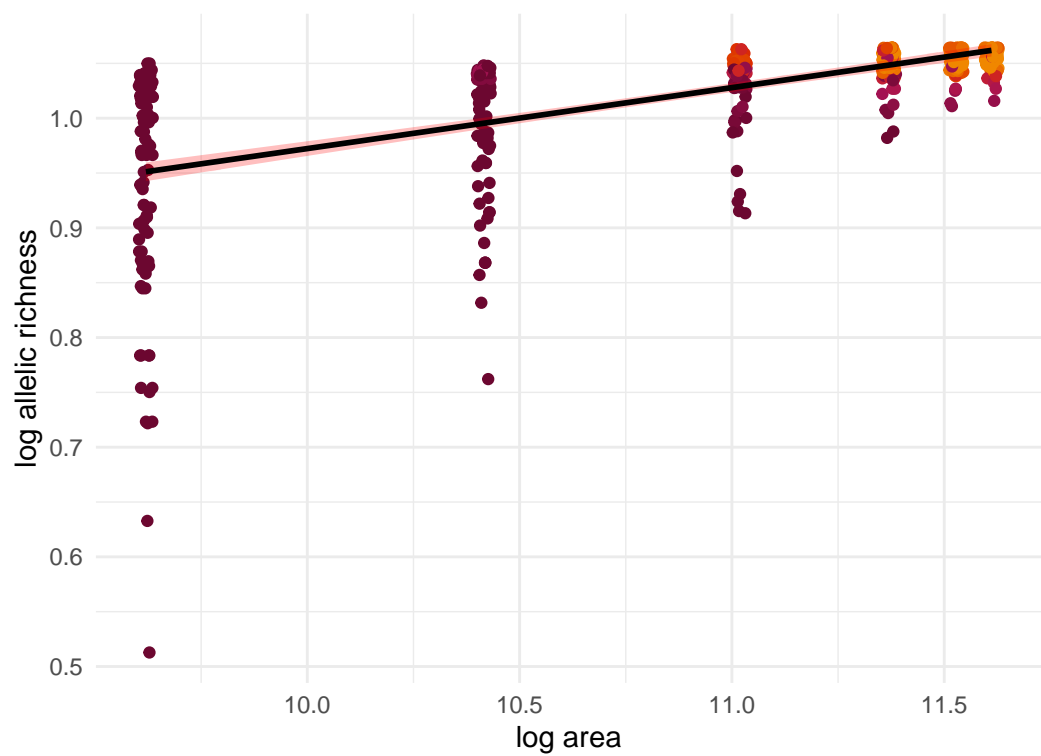
Lynx canadensis; $z=0.005$



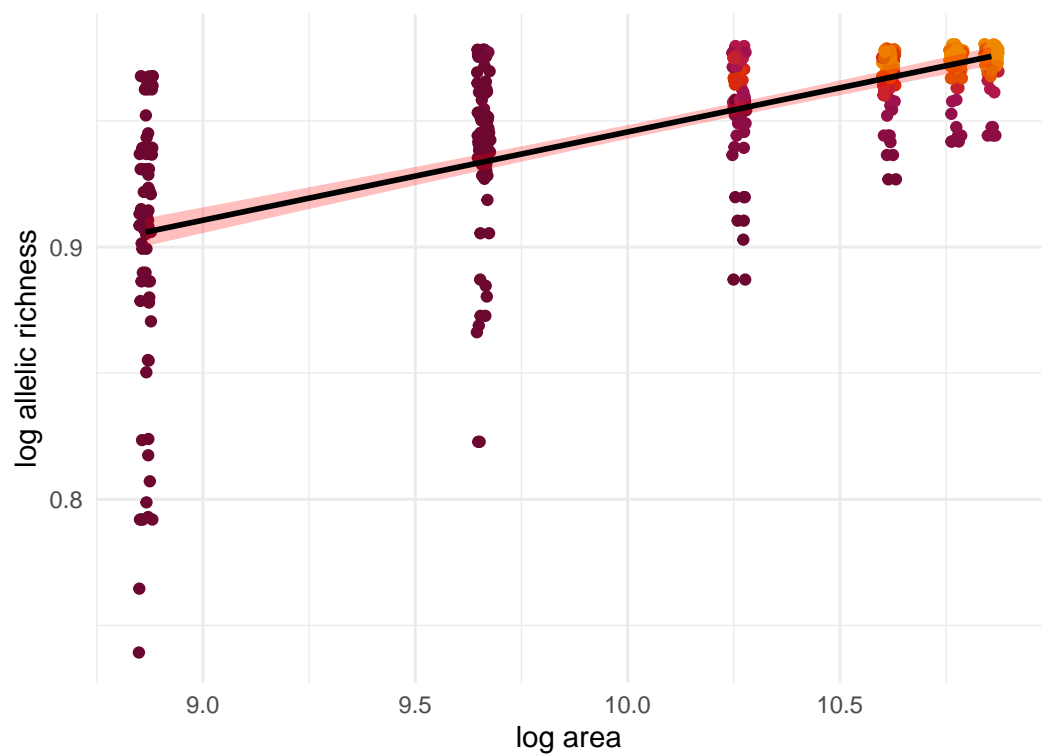
Felis silvestris; $z=0.037$



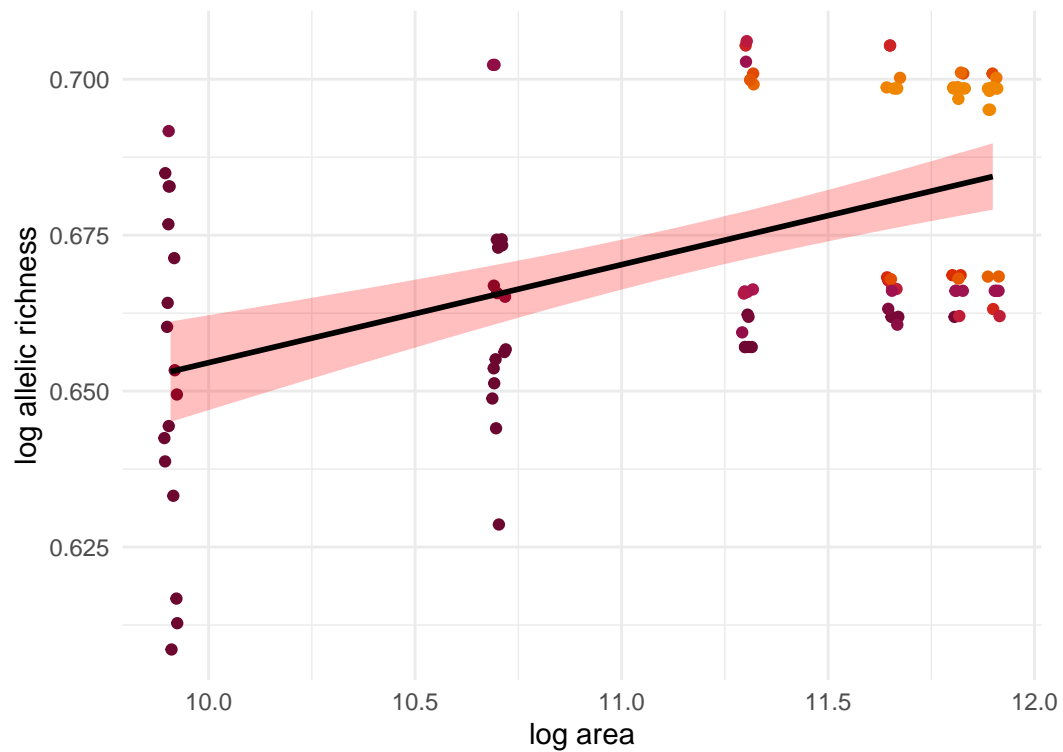
Ascapus montanus; $z=0.056$



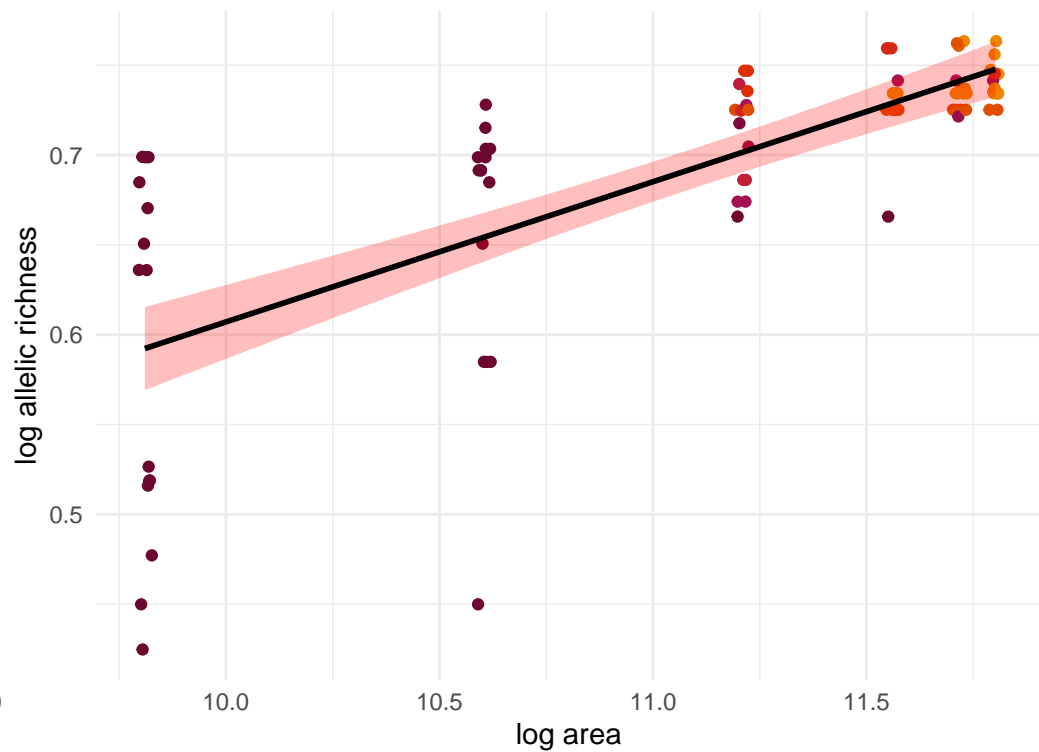
Ambystoma barbouri; $z=0.035$



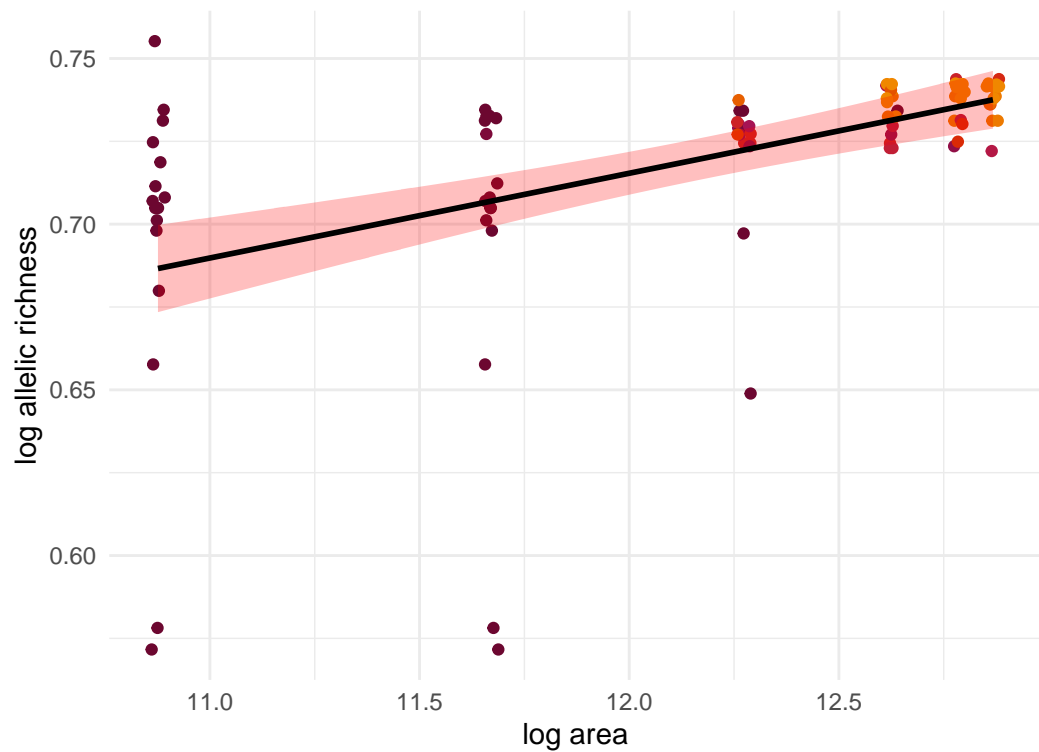
Strix occidentalis; $z=0.016$



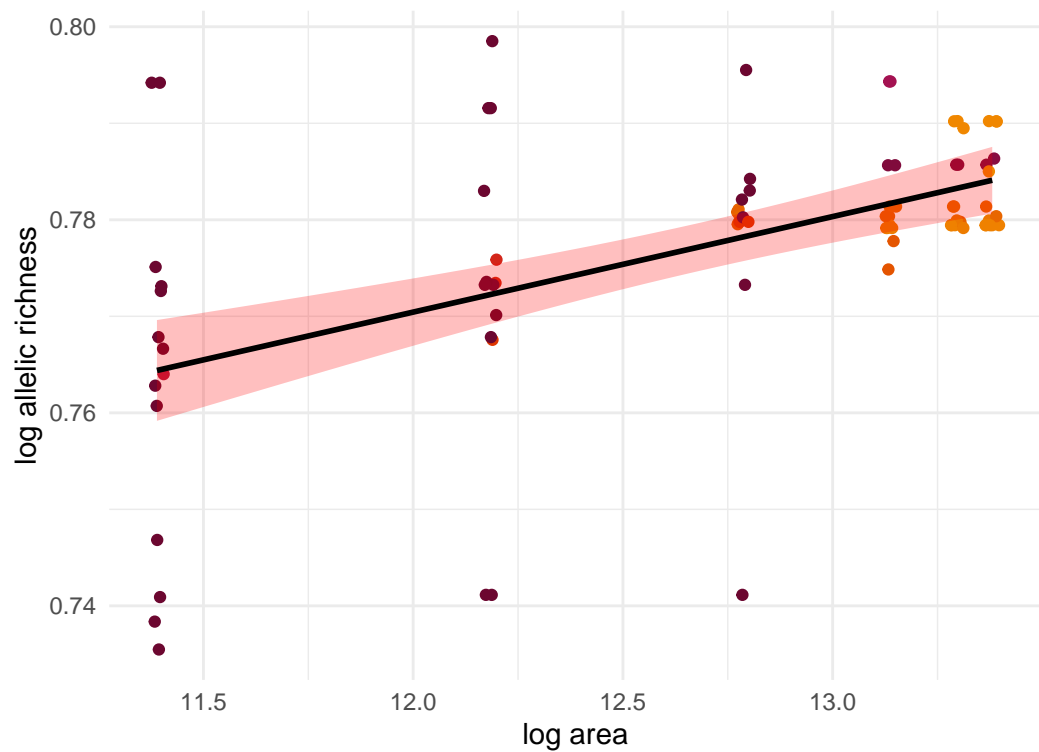
Liolaemus tenuis; $z=0.078$



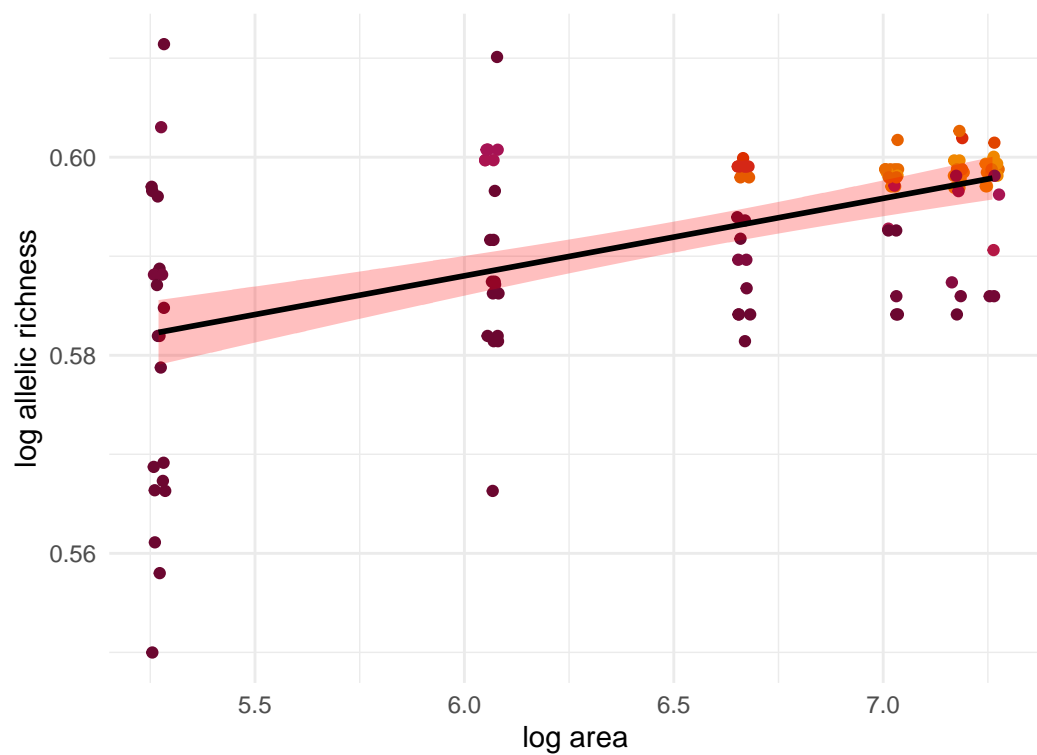
Alces alces; $z=0.026$



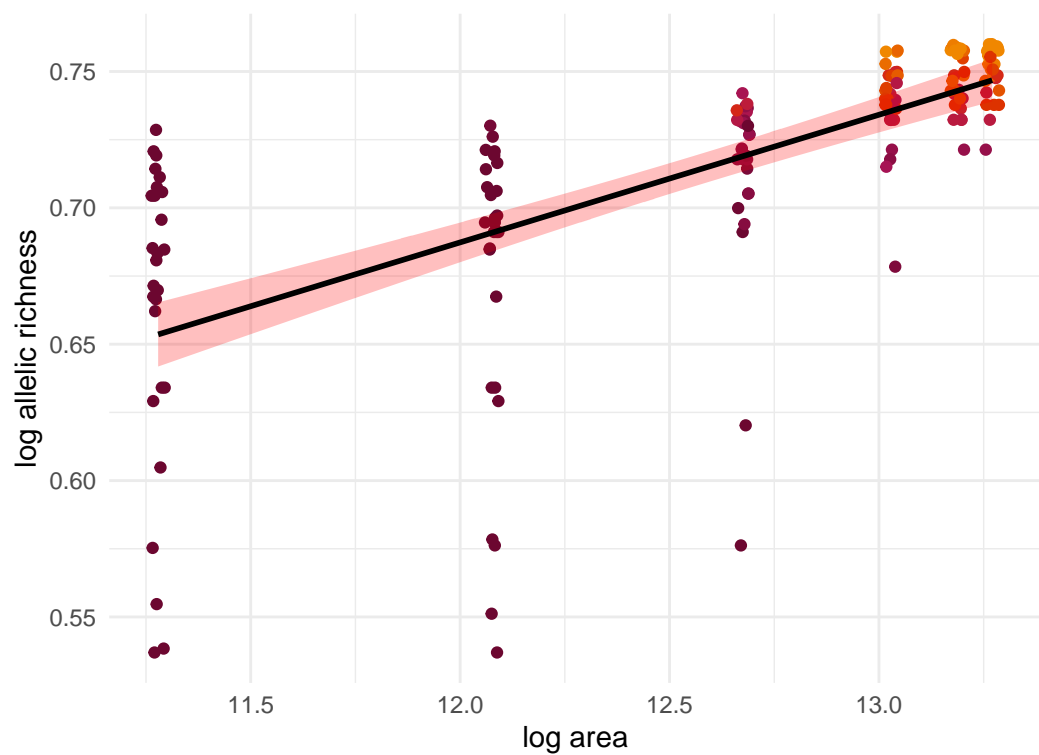
Ursus maritimus; $z=0.01$



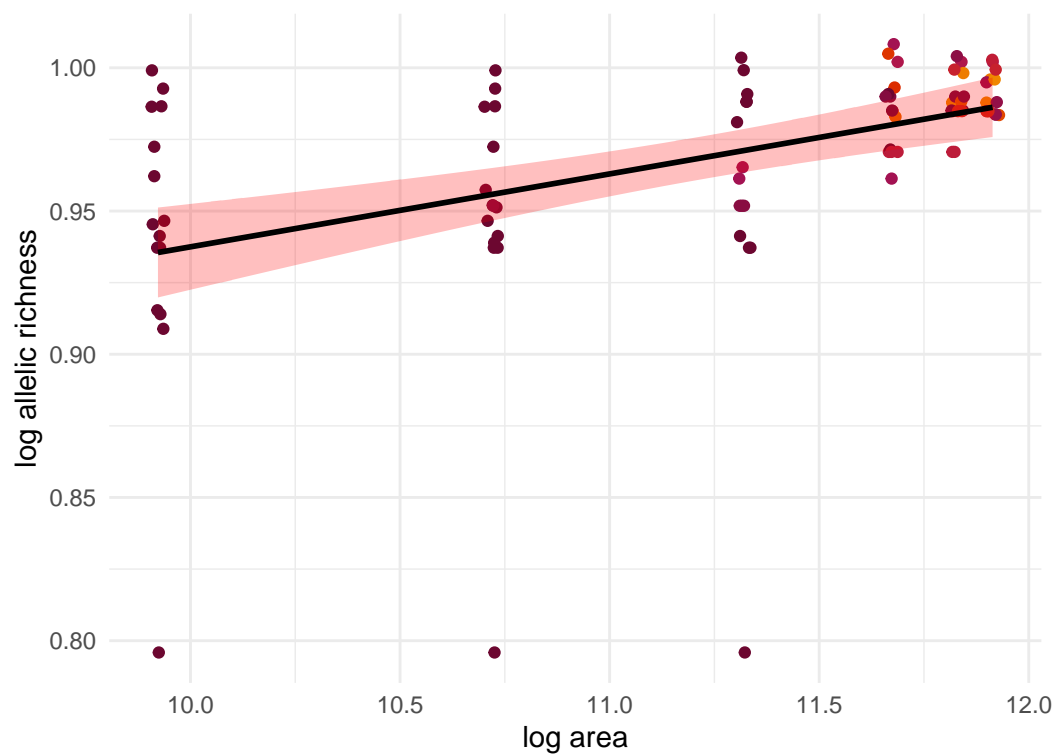
Plethodon albagula; $z=0.008$



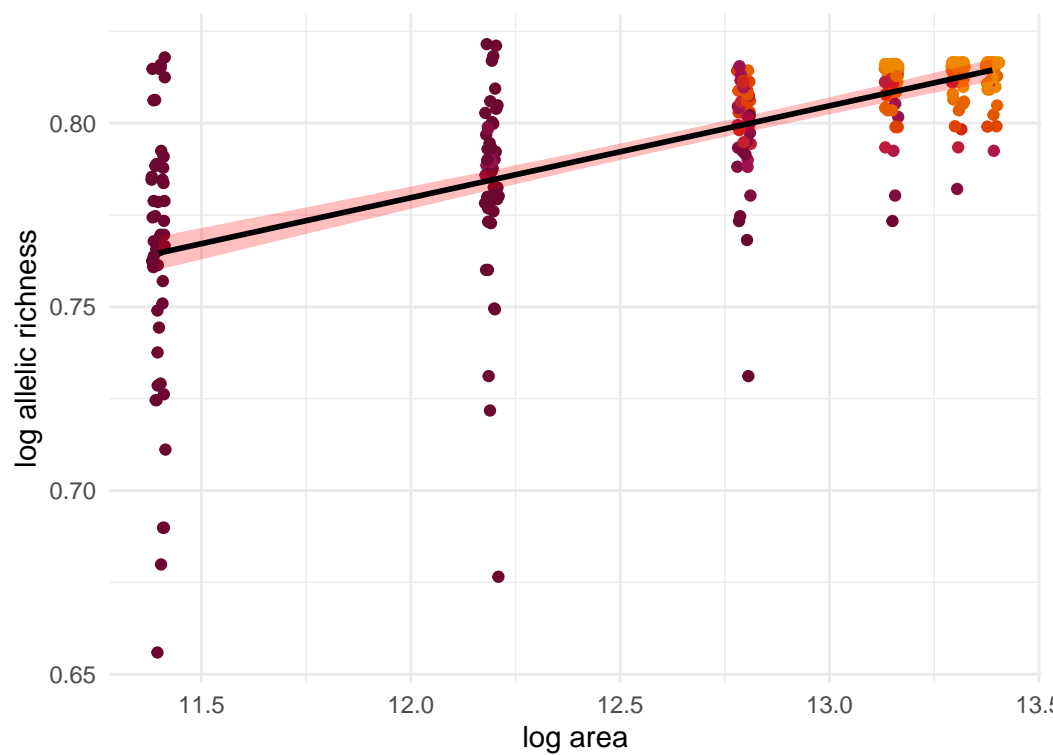
Ursus americanus; $z=0.047$



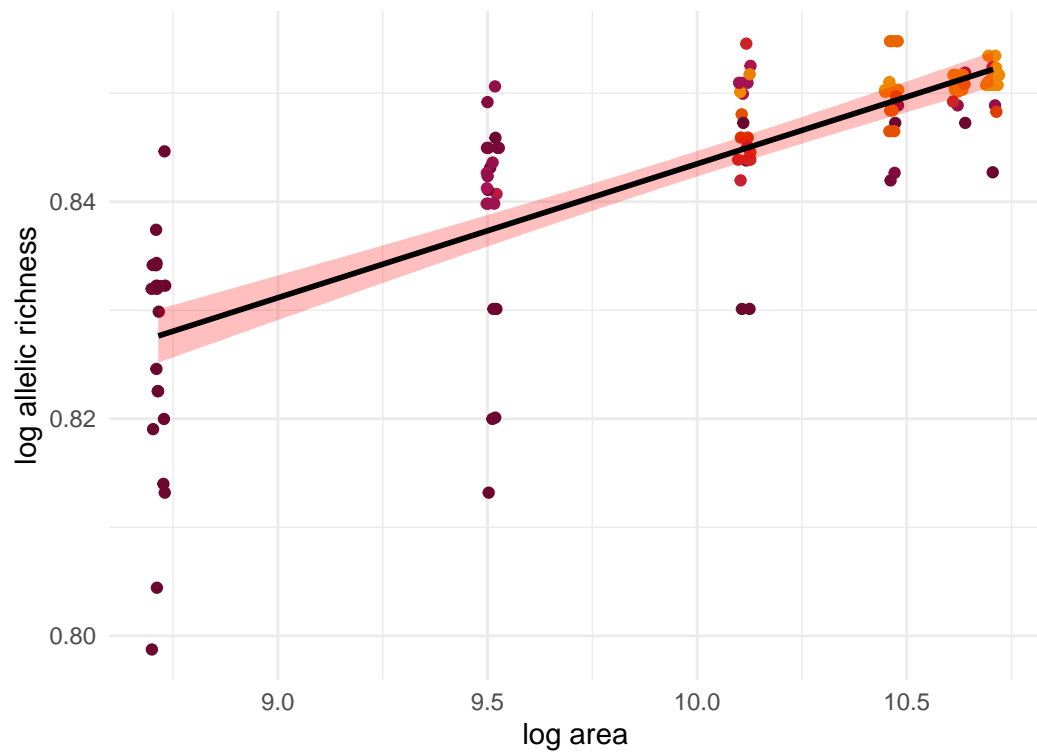
Myotis escaleraei; $z=0.025$



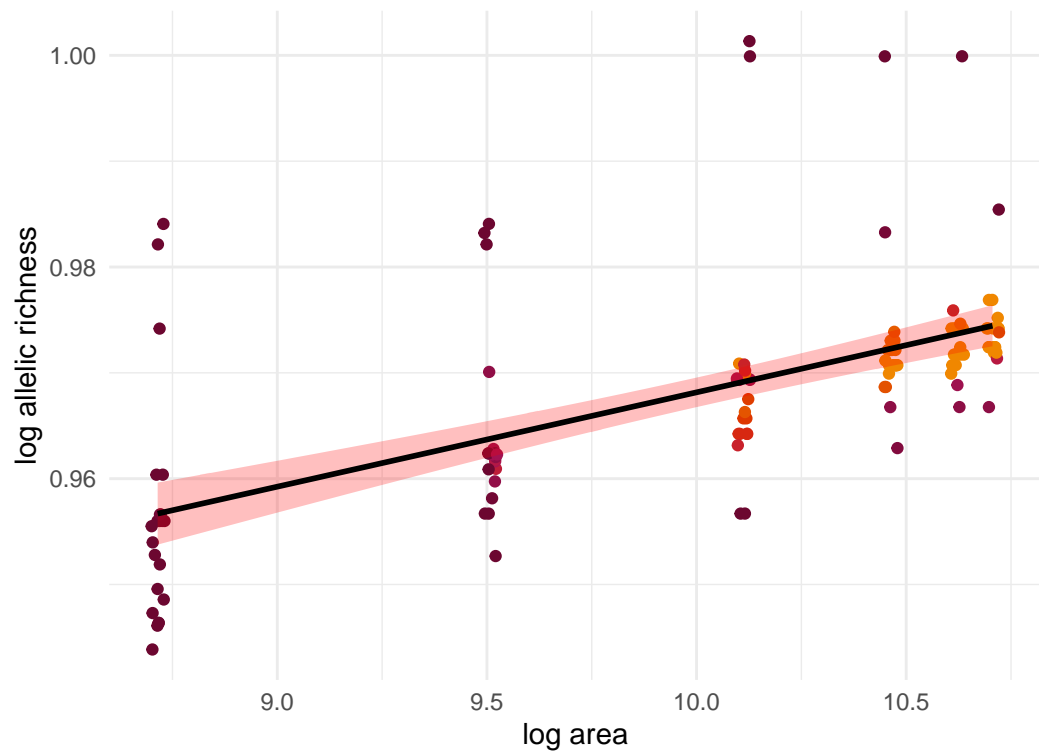
Lynx rufus; $z=0.025$



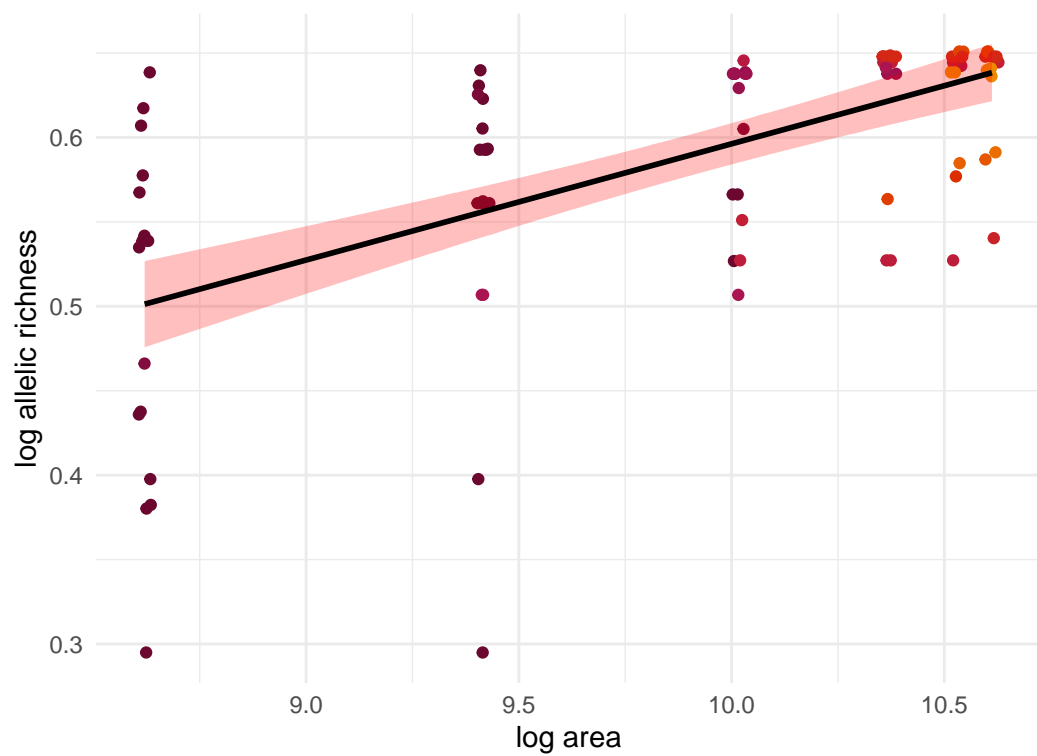
Ambystoma maculatum; $z=0.012$



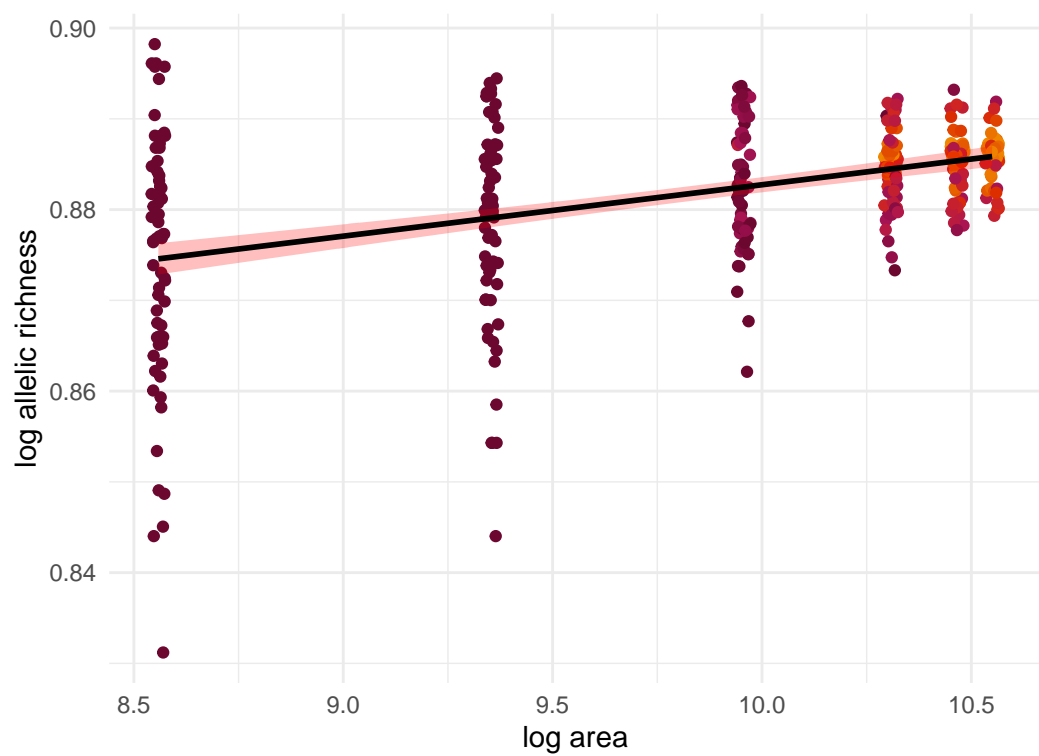
Rana sylvatica; $z=0.009$



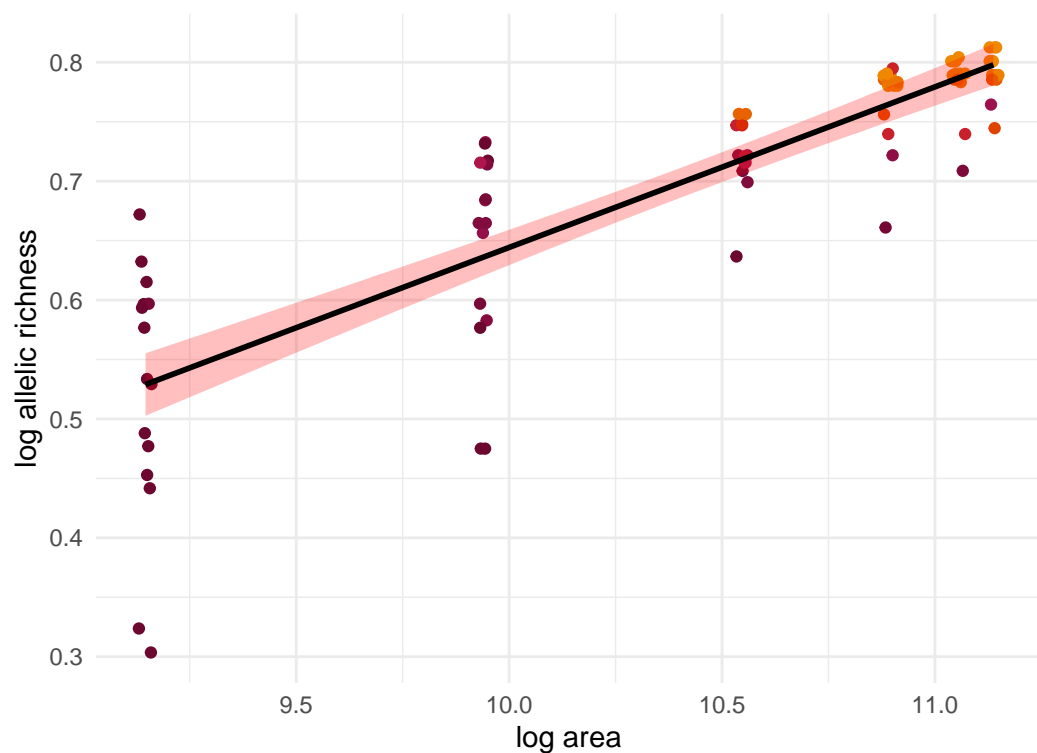
Rana draytonii; $z=0.069$



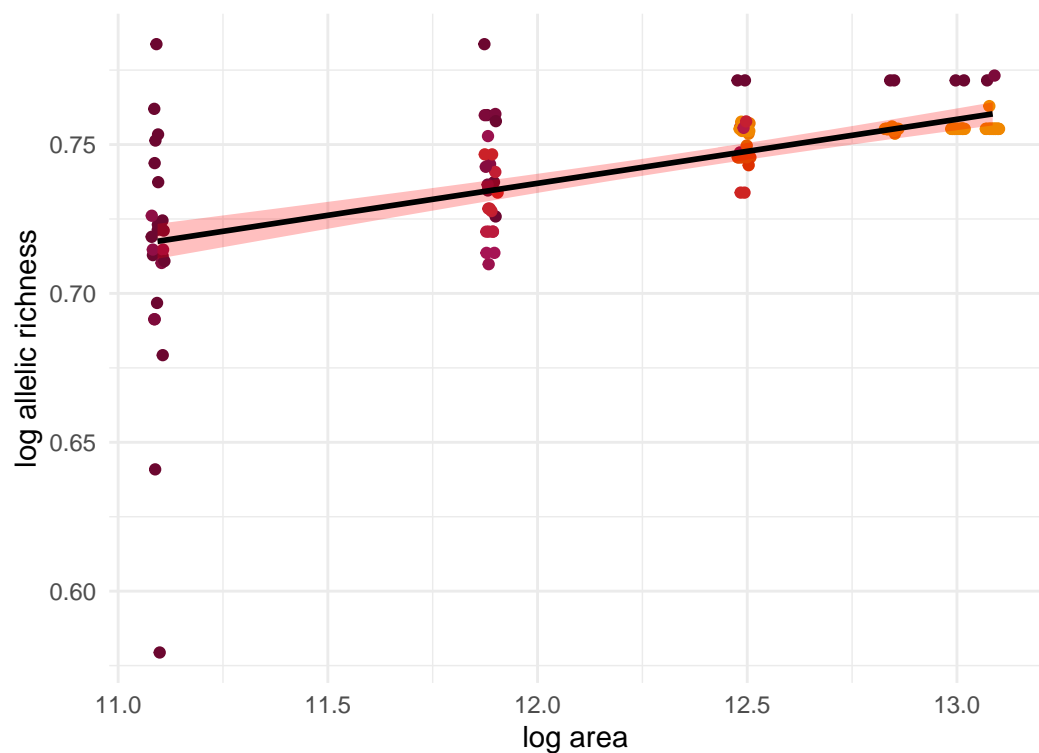
Odocoileus virginianus; $z=0.006$



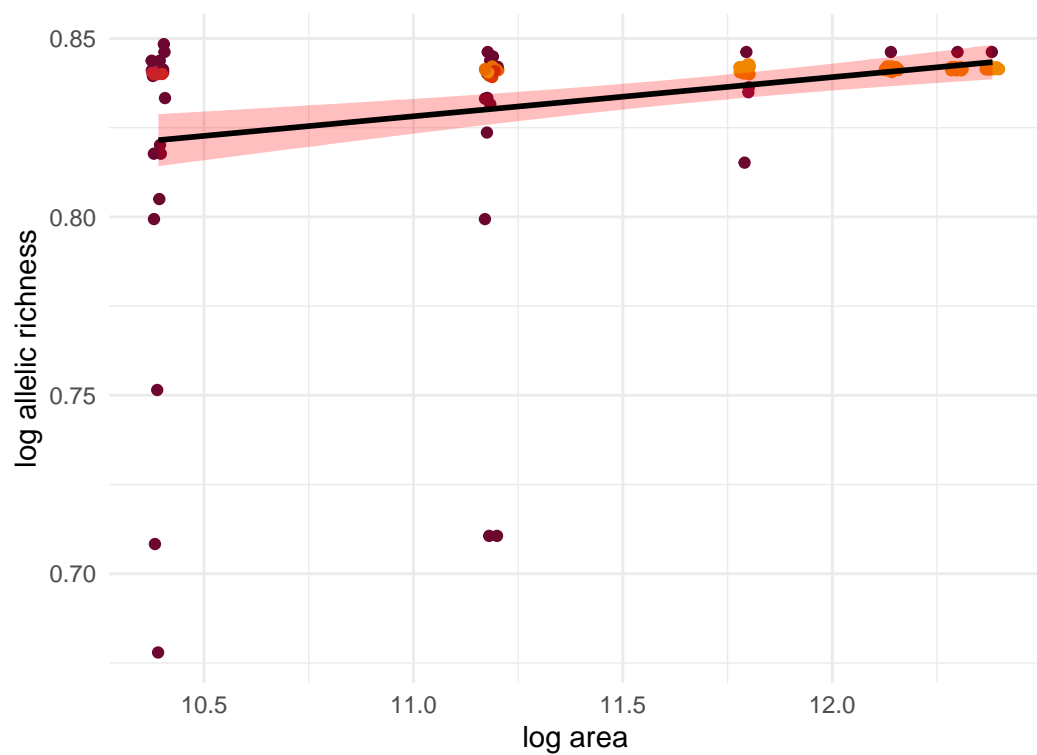
Hydromantes platycephalus; $z=0.135$



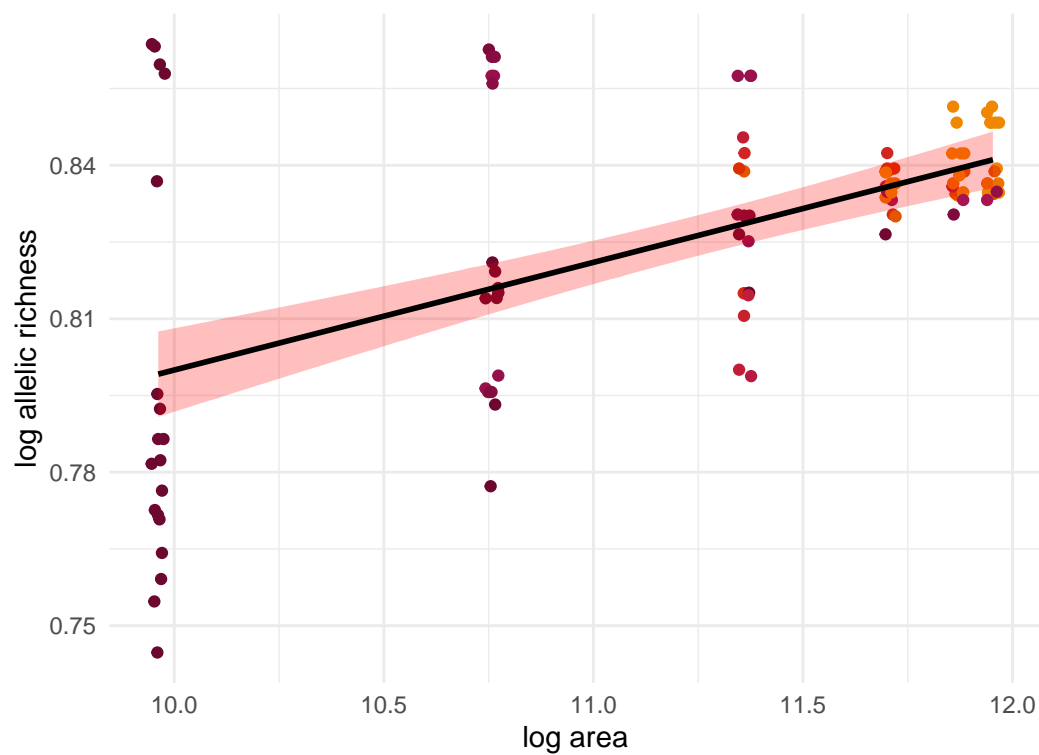
Rangifer tarandus; $z=0.021$



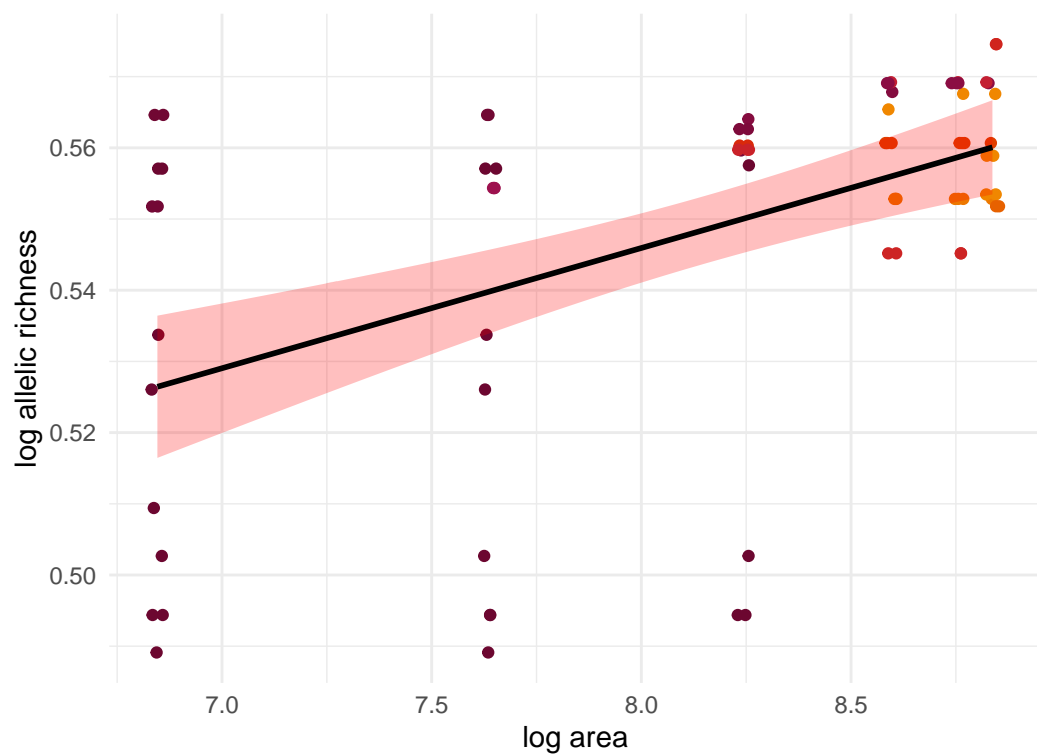
Rhinolophus ferrumequinum; $z=0.011$



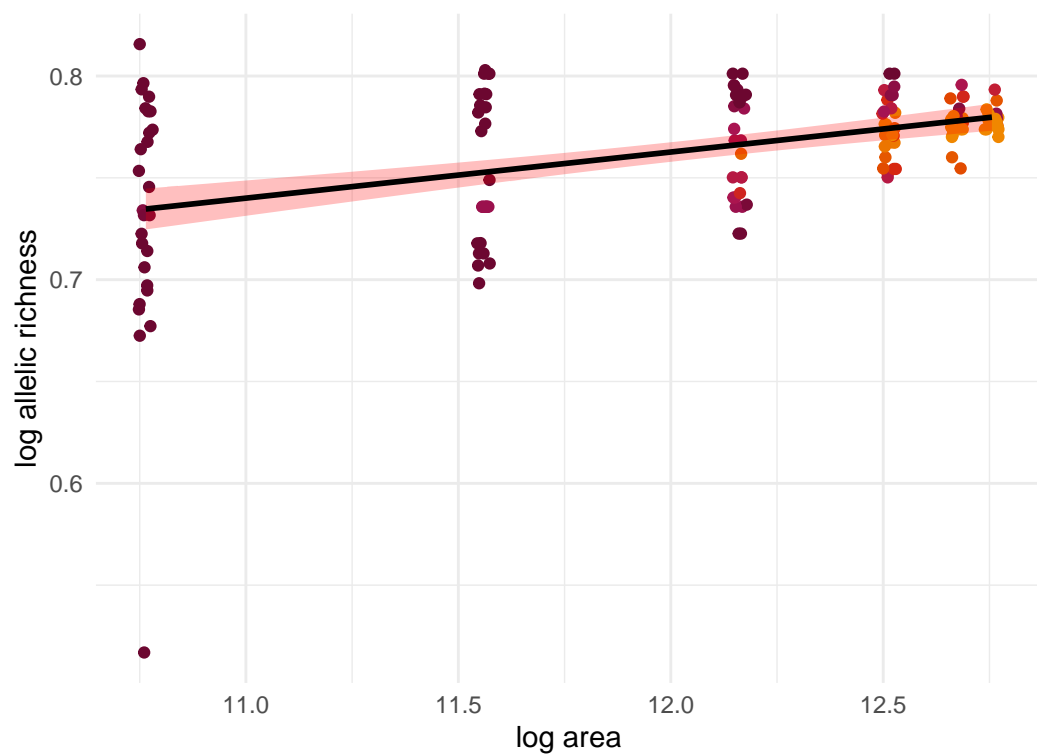
Dipsosaurus dorsalis; $z=0.021$



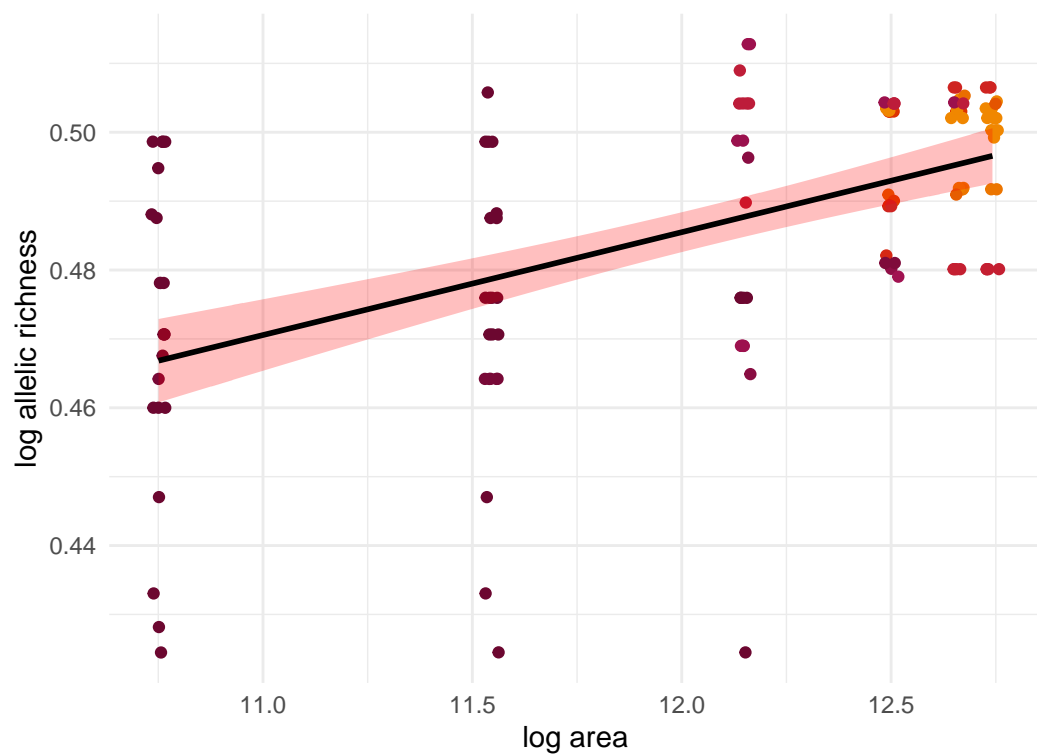
Uma inornata; $z=0.017$



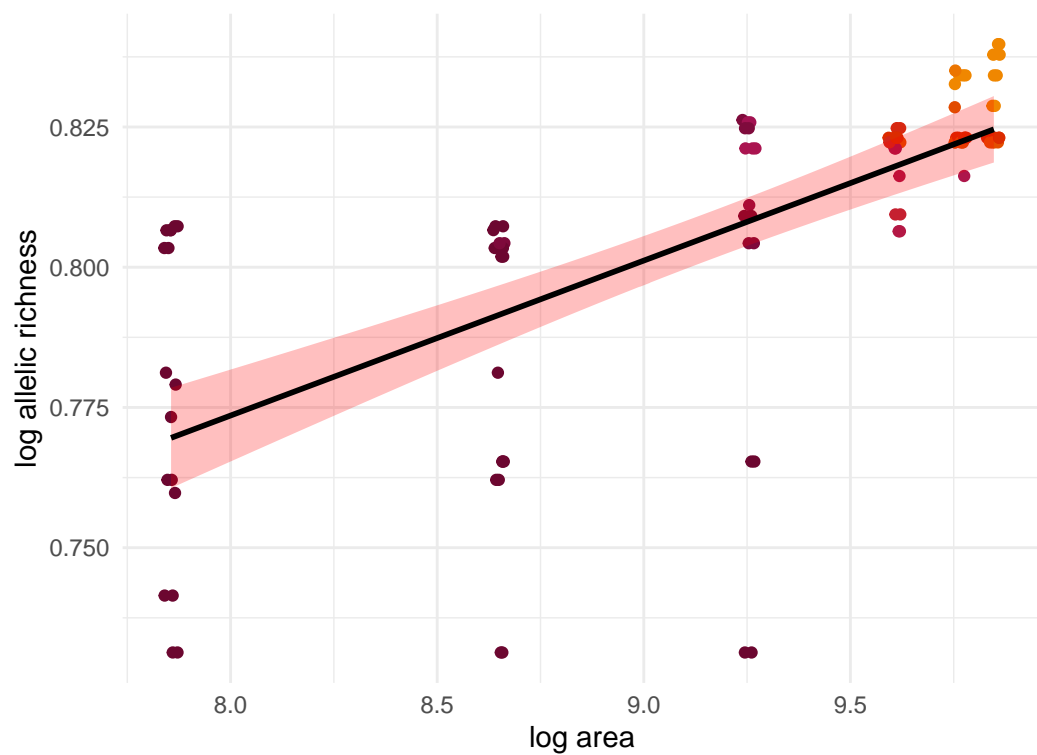
Rangifer tarandus; $z=0.023$



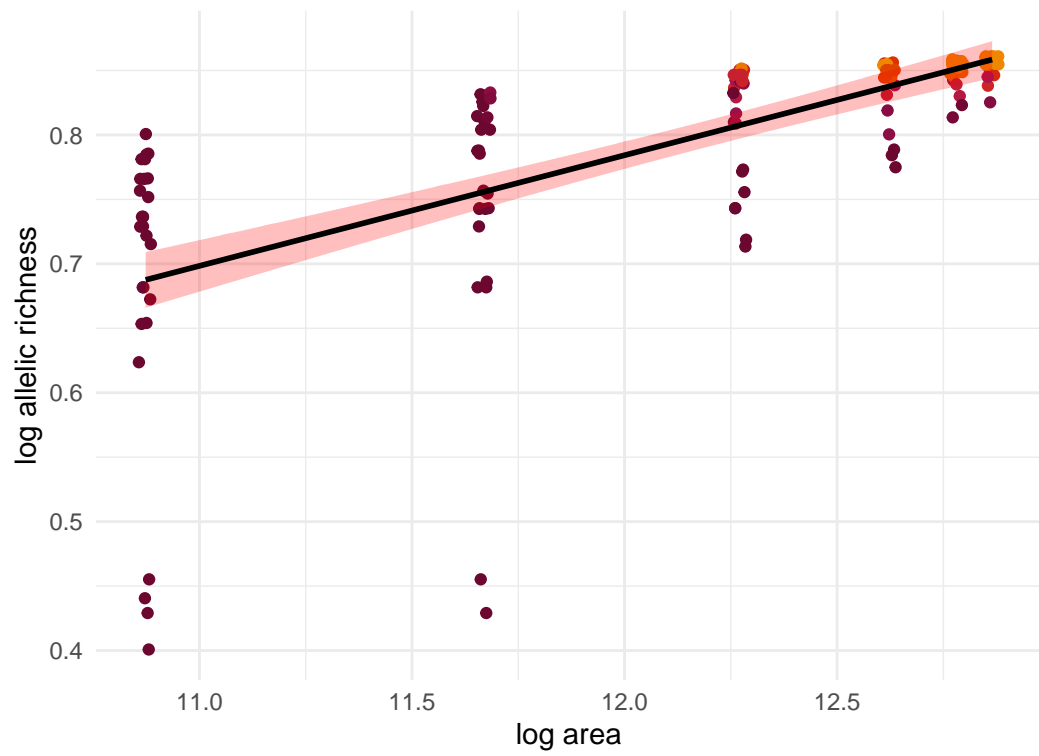
Miniopterus schreibersii; $z=0.015$



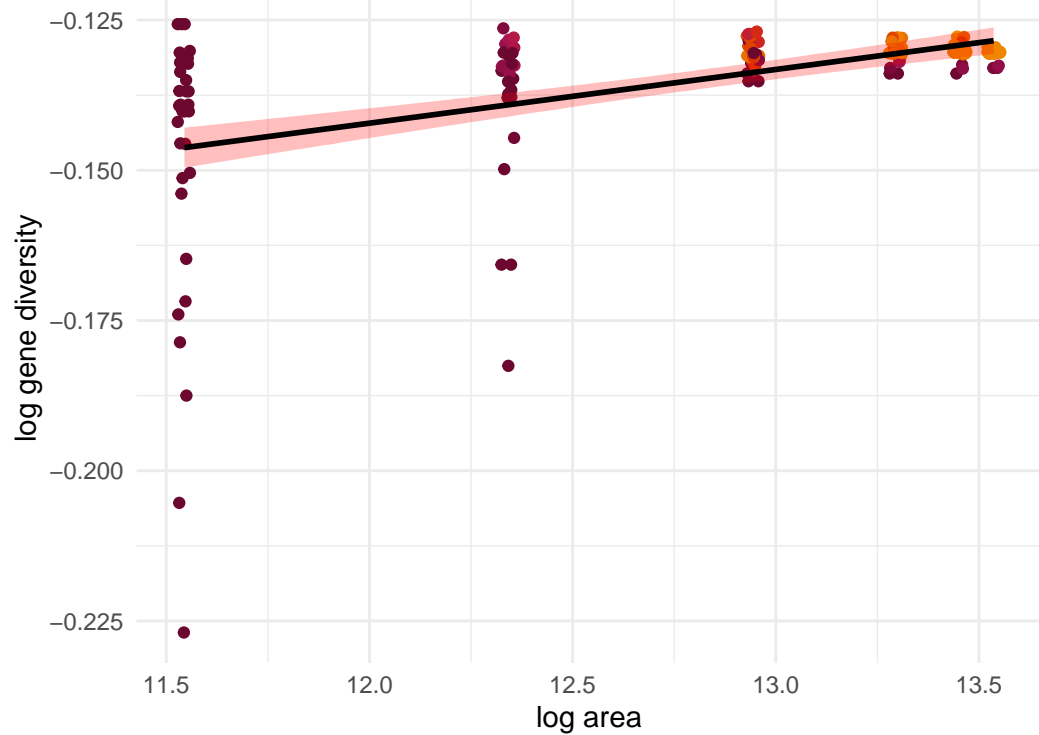
Sorex antinorii; $z=0.028$



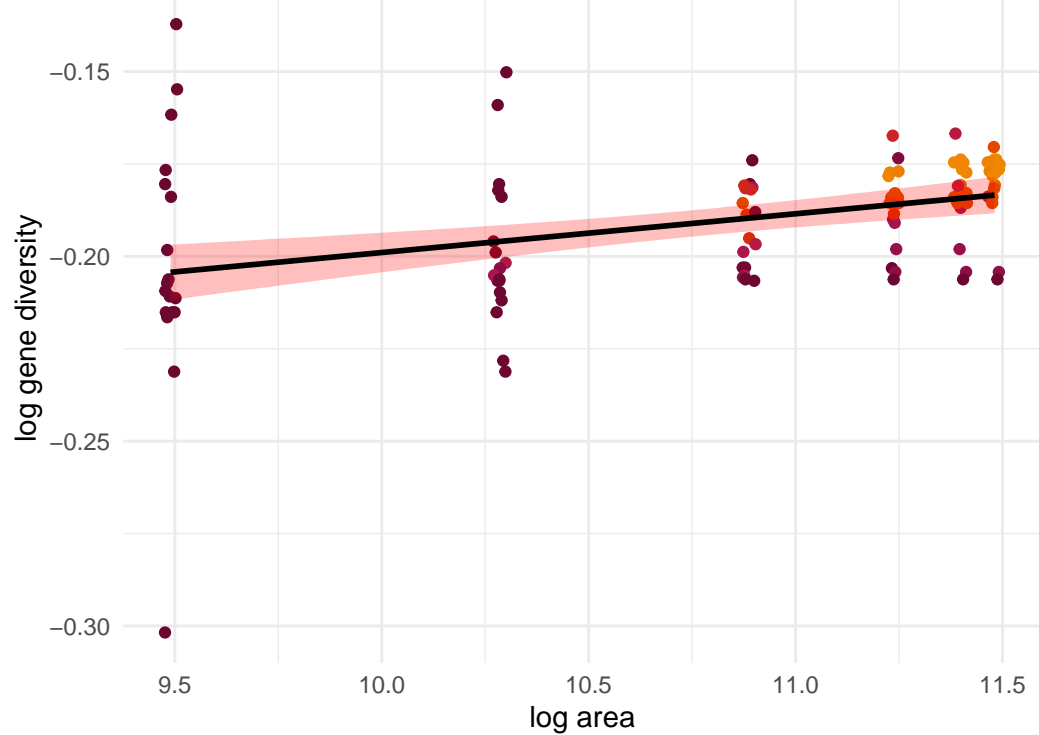
Cervus elaphus; $z=0.086$



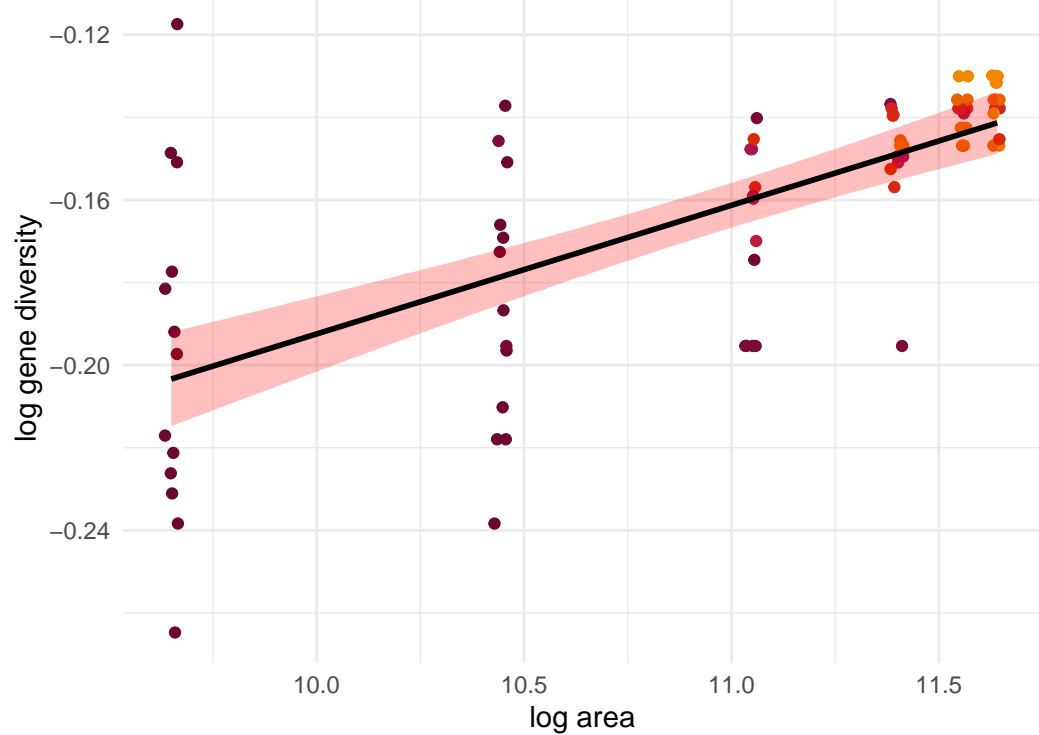
Poecile atricapillus; $z=0.009$



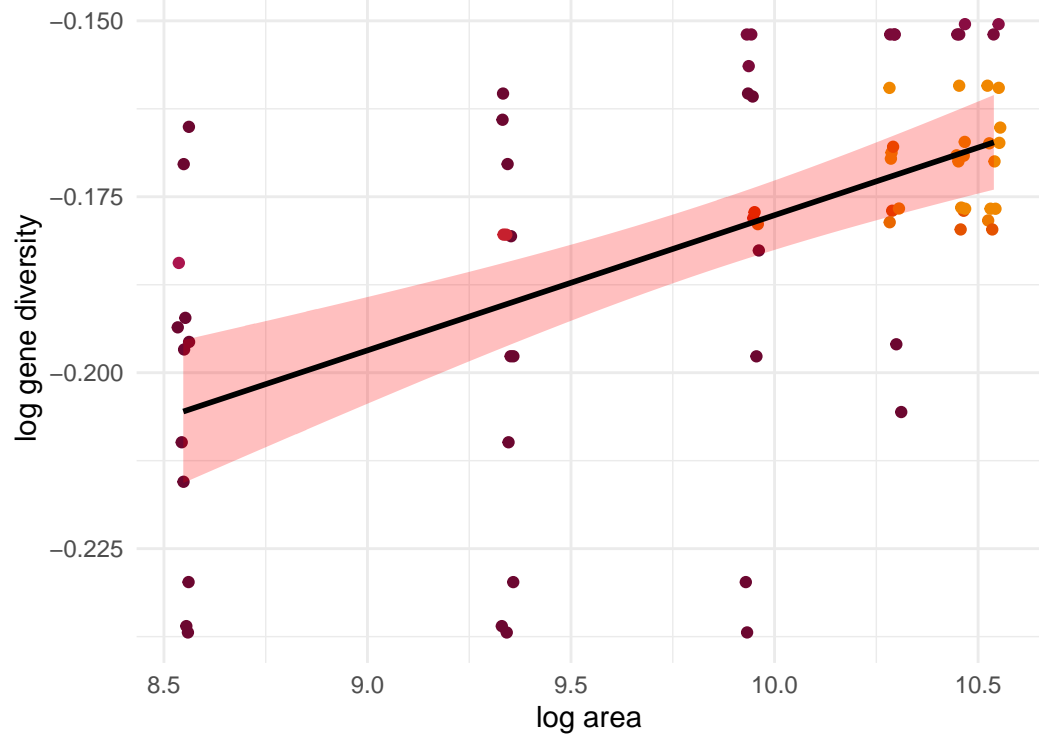
Sus scrofa; $z=0.01$



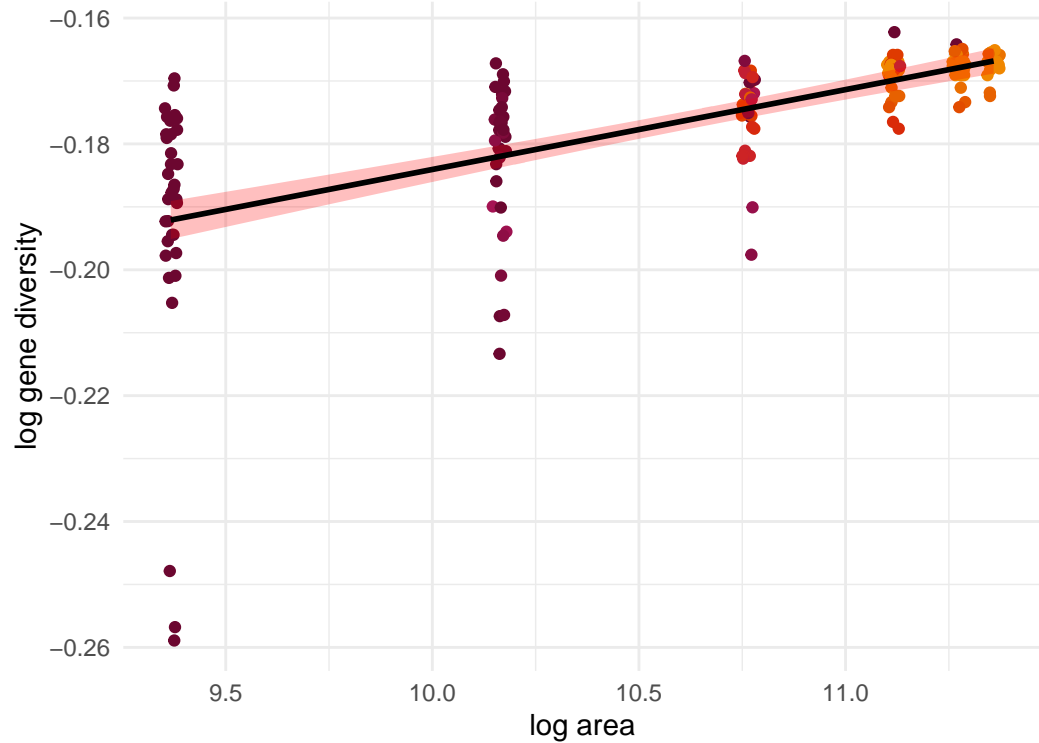
Capreolus capreolus; $z=0.031$



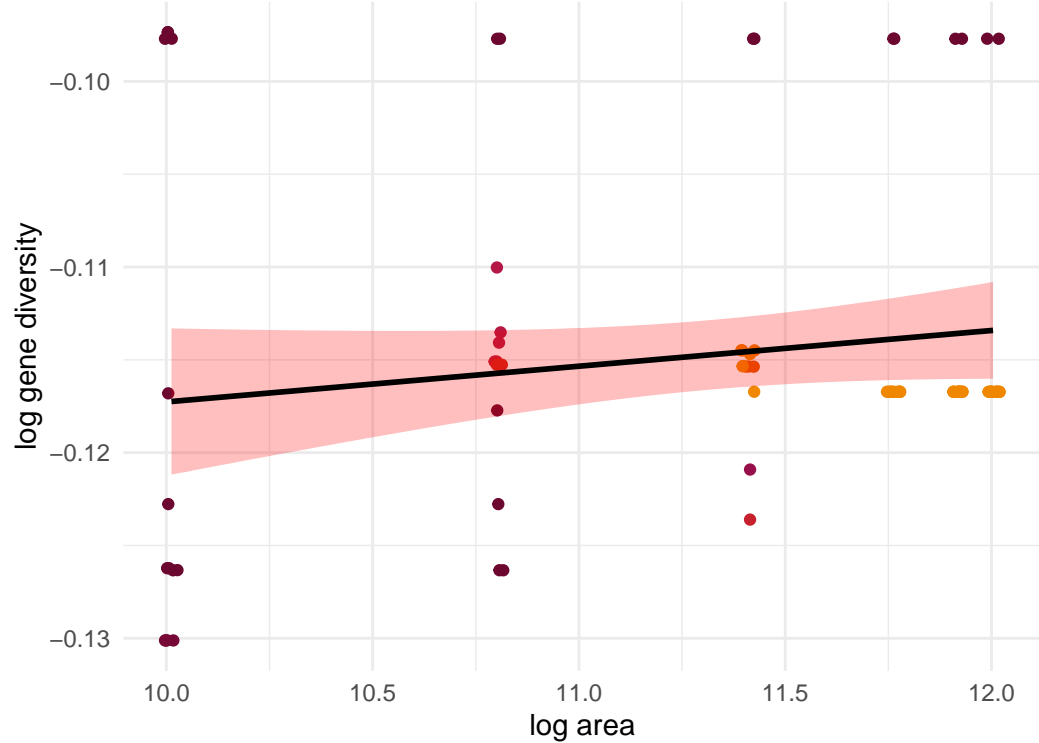
Campylorhynchus brunneicapillus; $z=0.019$



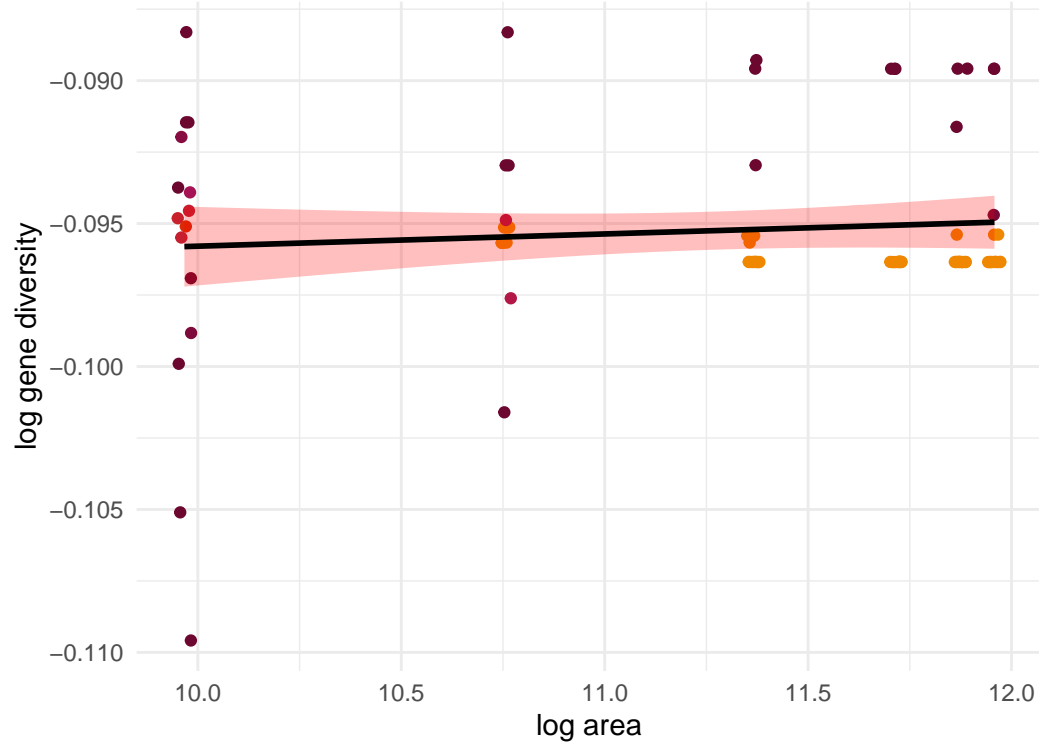
Pekania pennanti; z=0.013



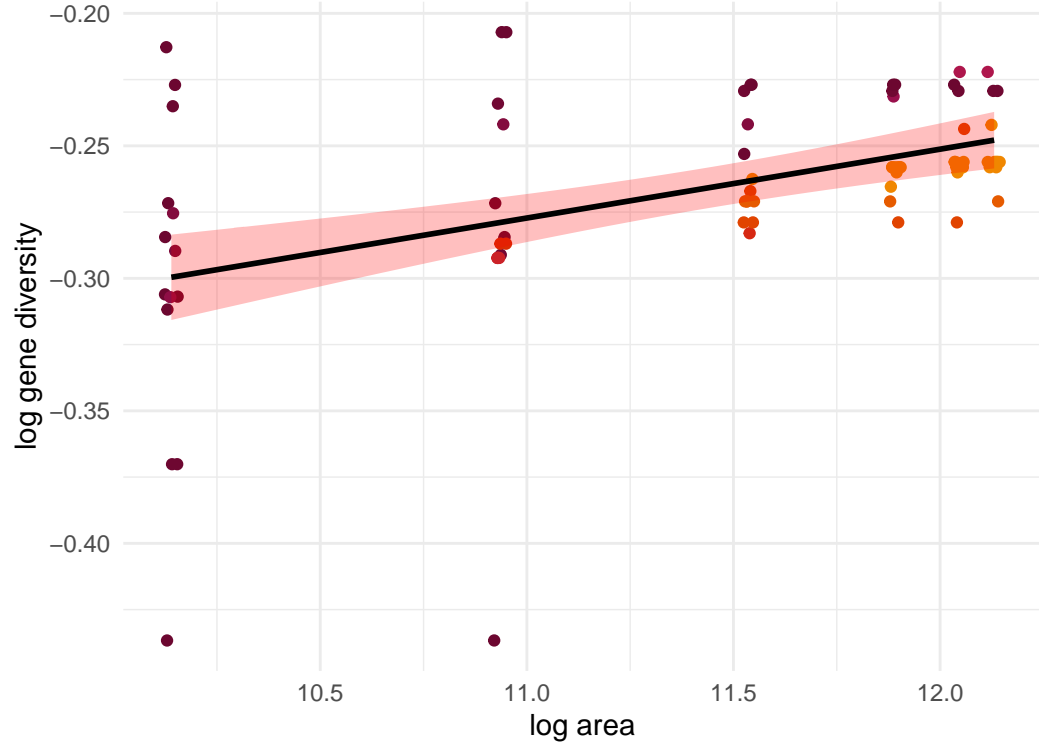
Nyctalus leisleri; z=NA



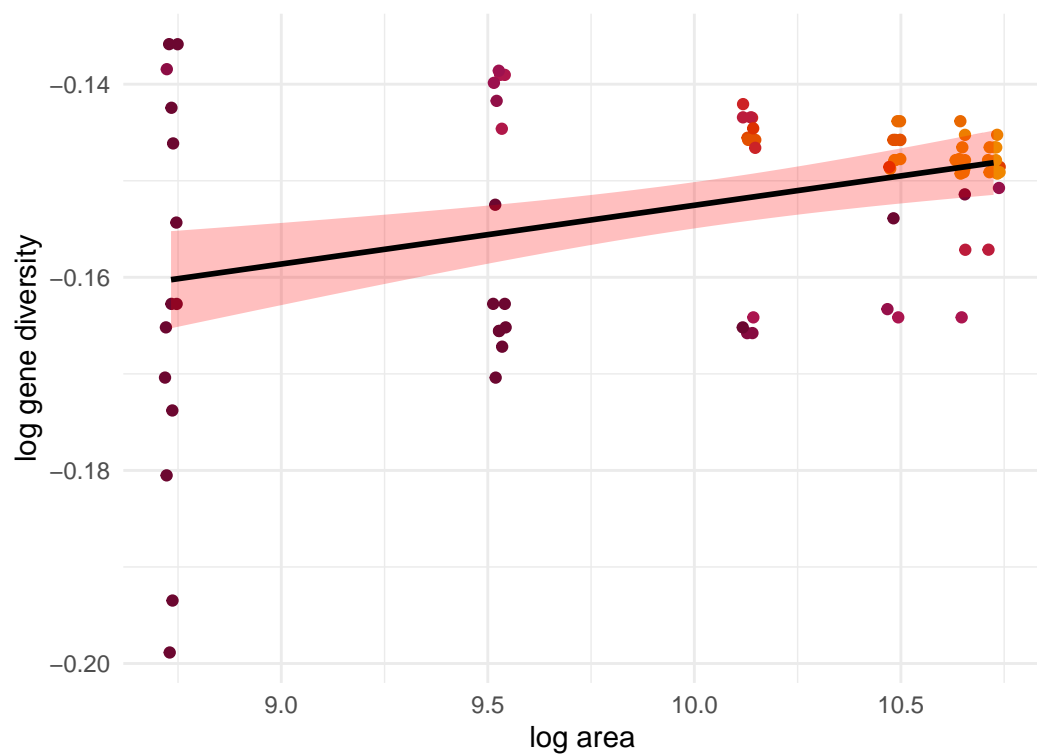
Myotis lucifugus; z=NA



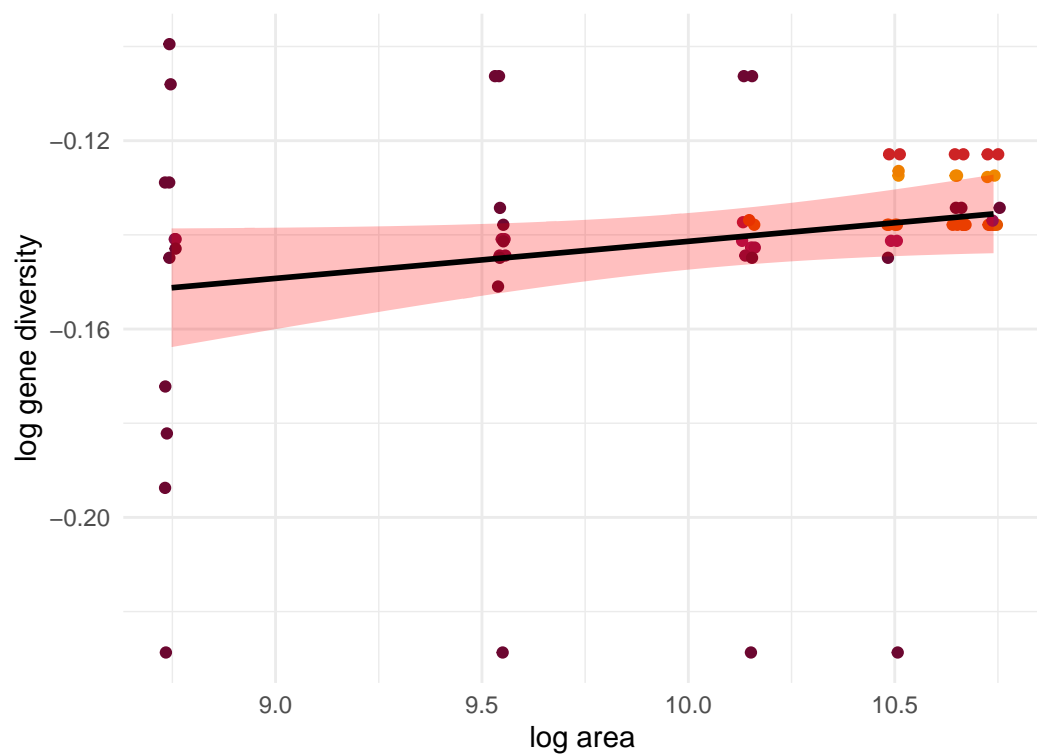
Vicugna vicugna; z=0.026



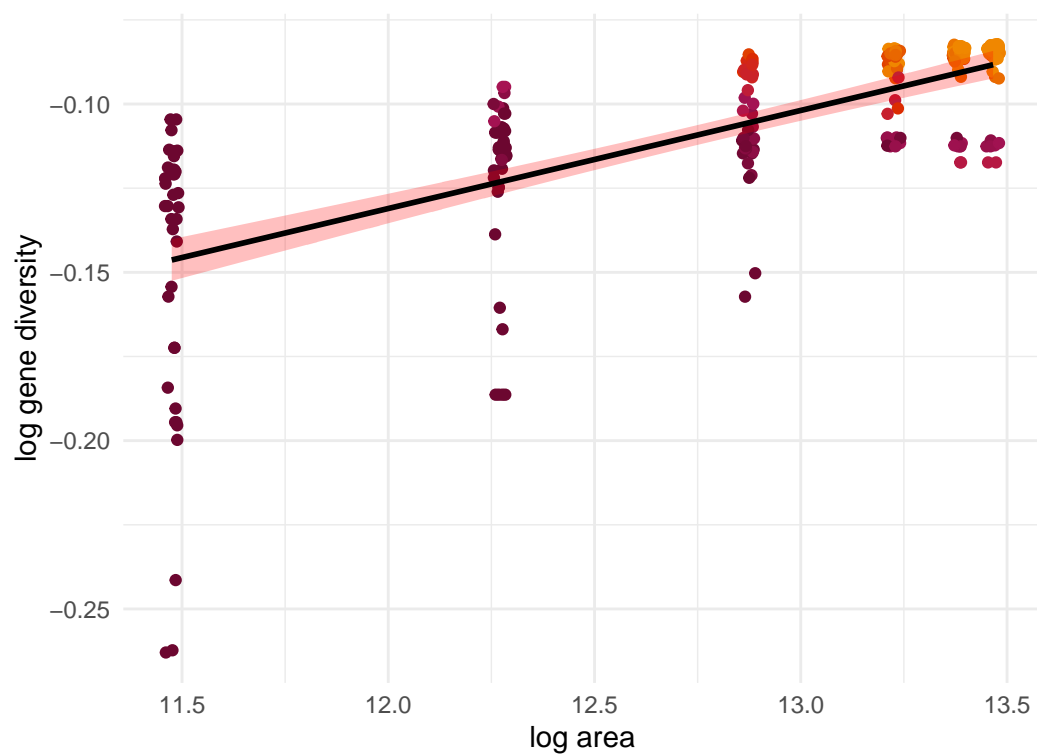
Tamiasciurus douglasii; $z=0.006$



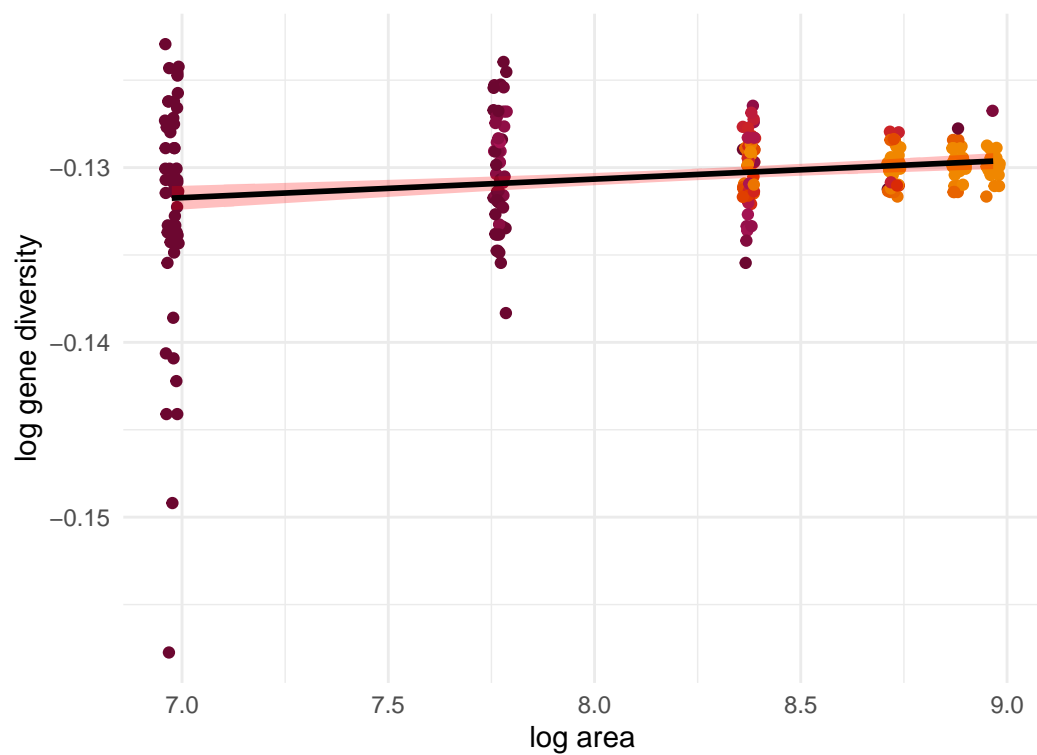
Tamiasciurus hudsonicus; $z=NA$



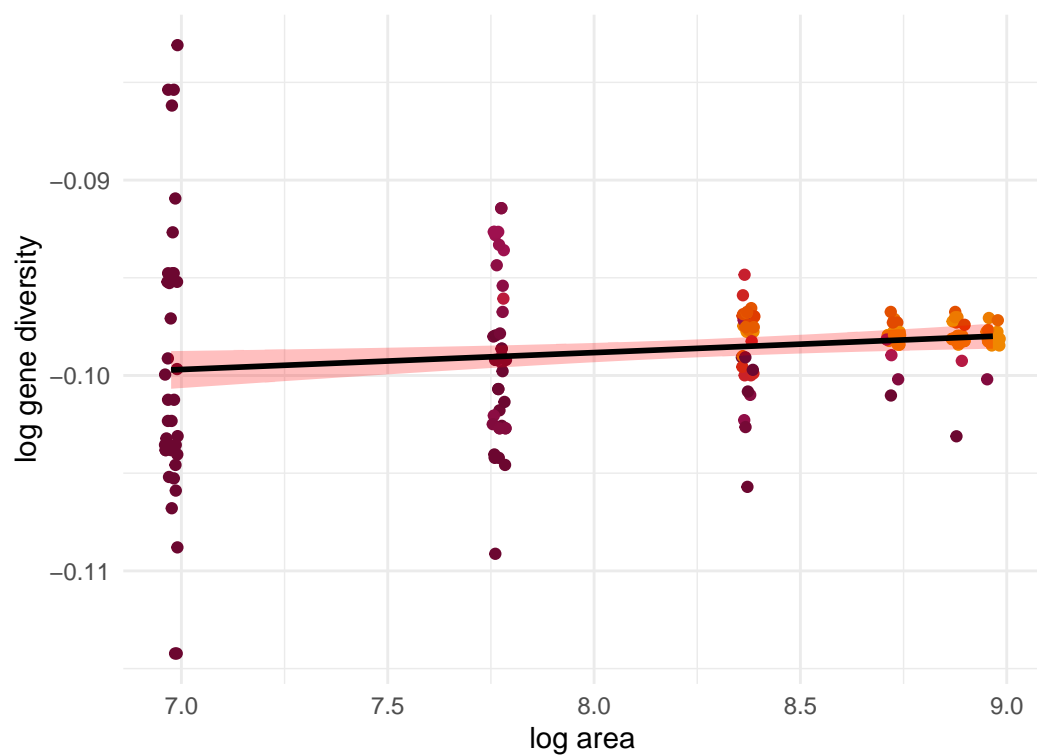
Lepus americanus; $z=0.029$



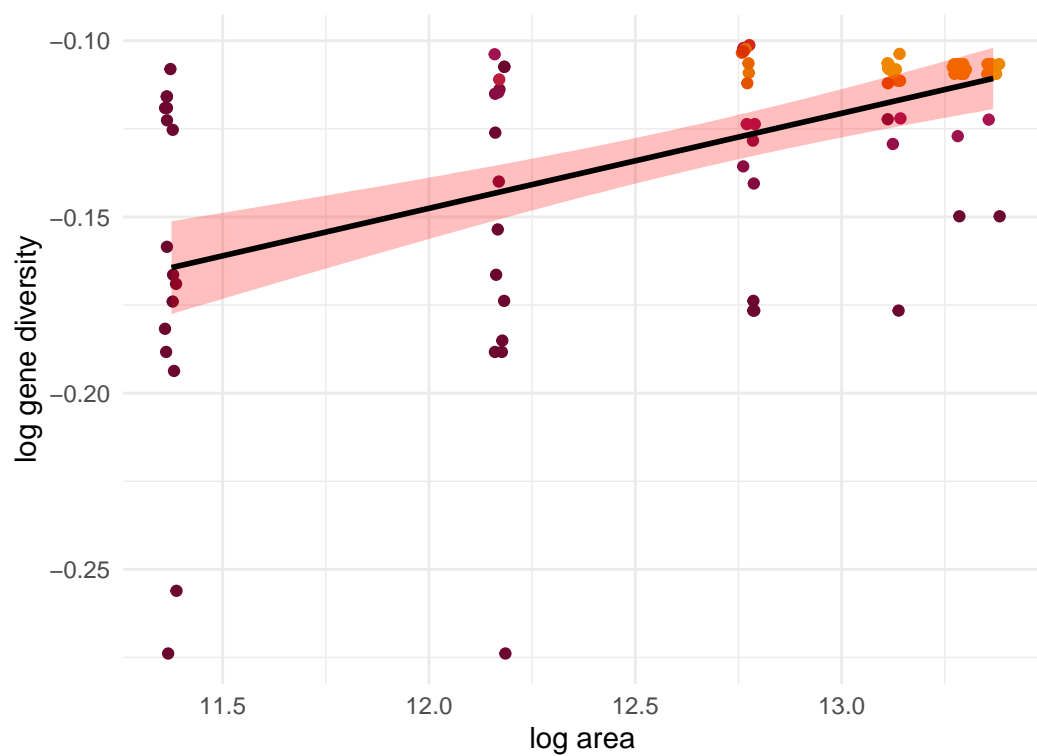
Ambystoma maculatum; $z=0.001$



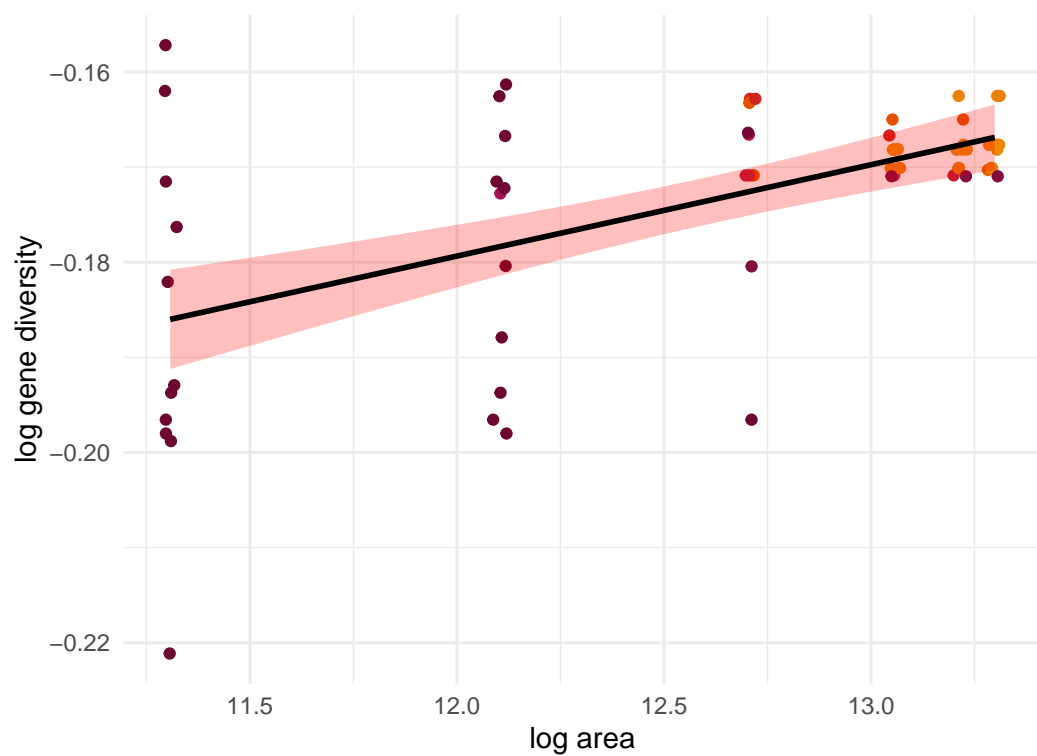
Lithobates sylvaticus; $z=0.001$



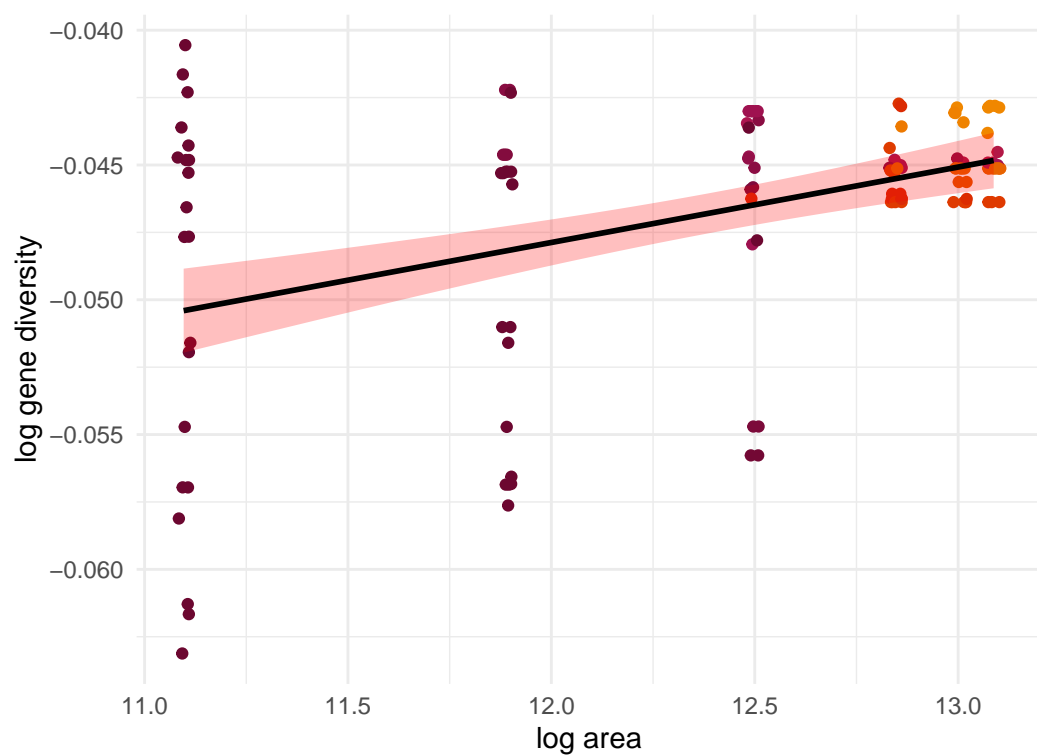
Ursus arctos; $z=0.027$



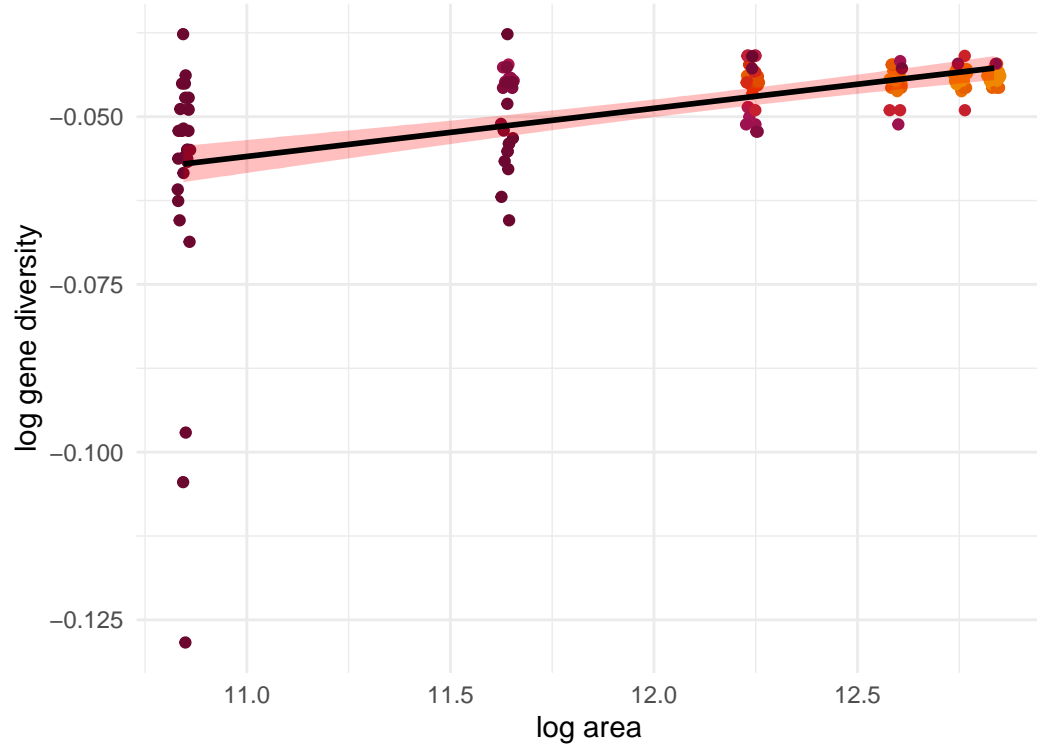
Ursus maritimus; $z=0.01$



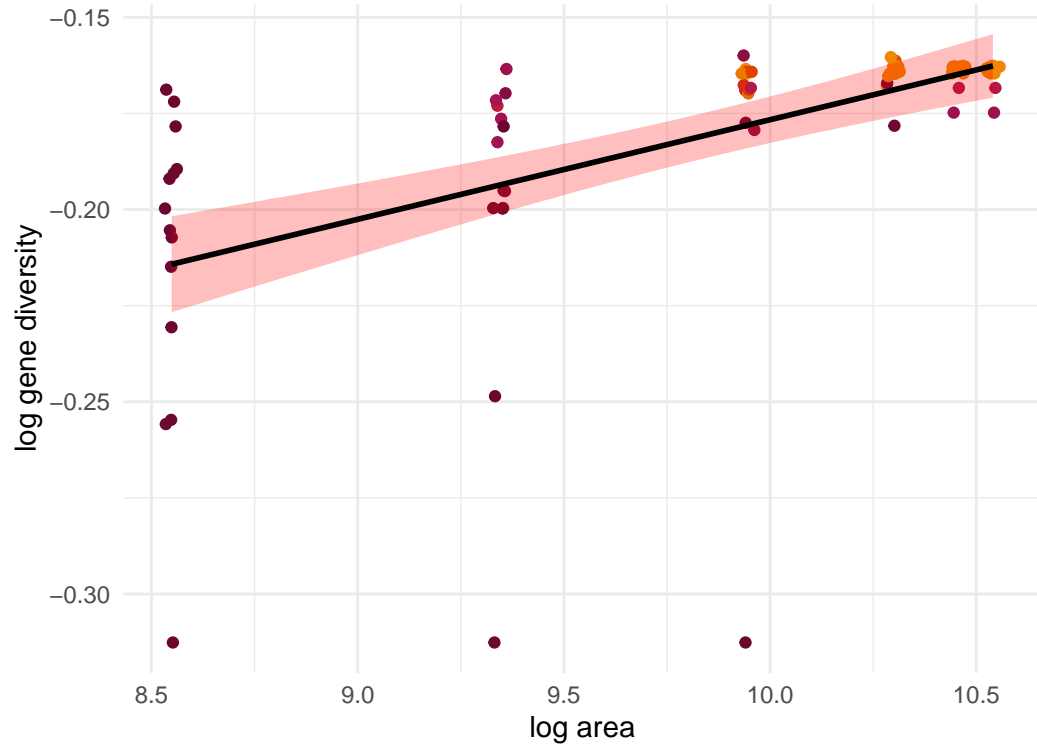
Myotis lucifugus; $z=0.003$



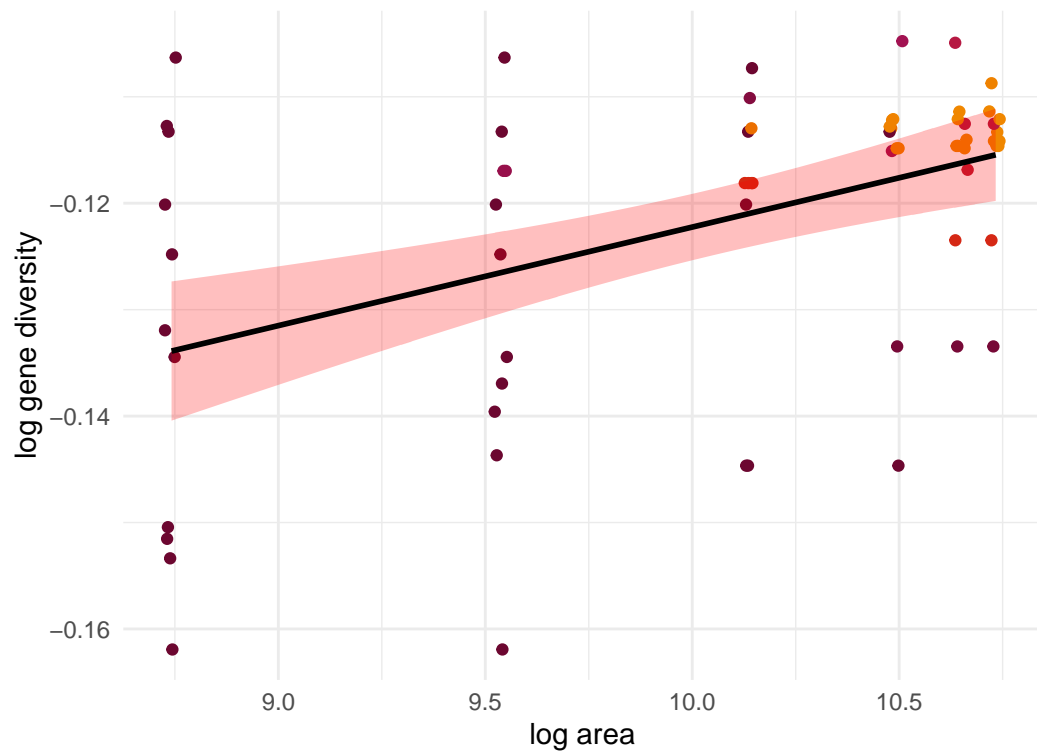
Lithobates sylvaticus; $z=0.007$



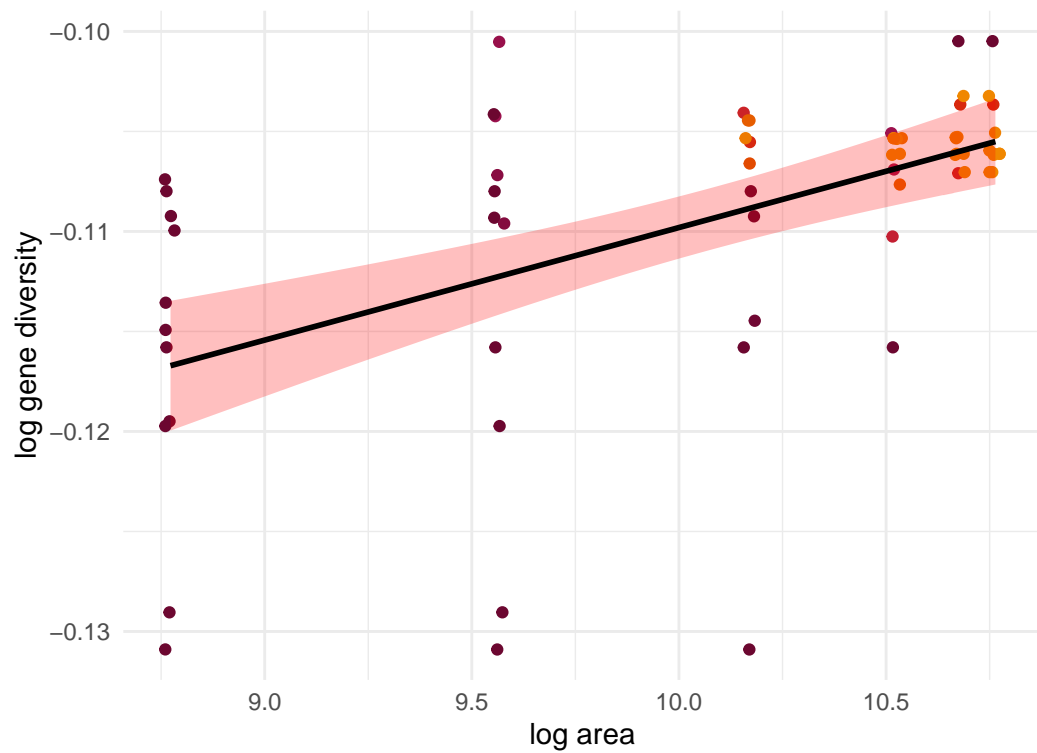
Ovis canadensis; $z=0.026$



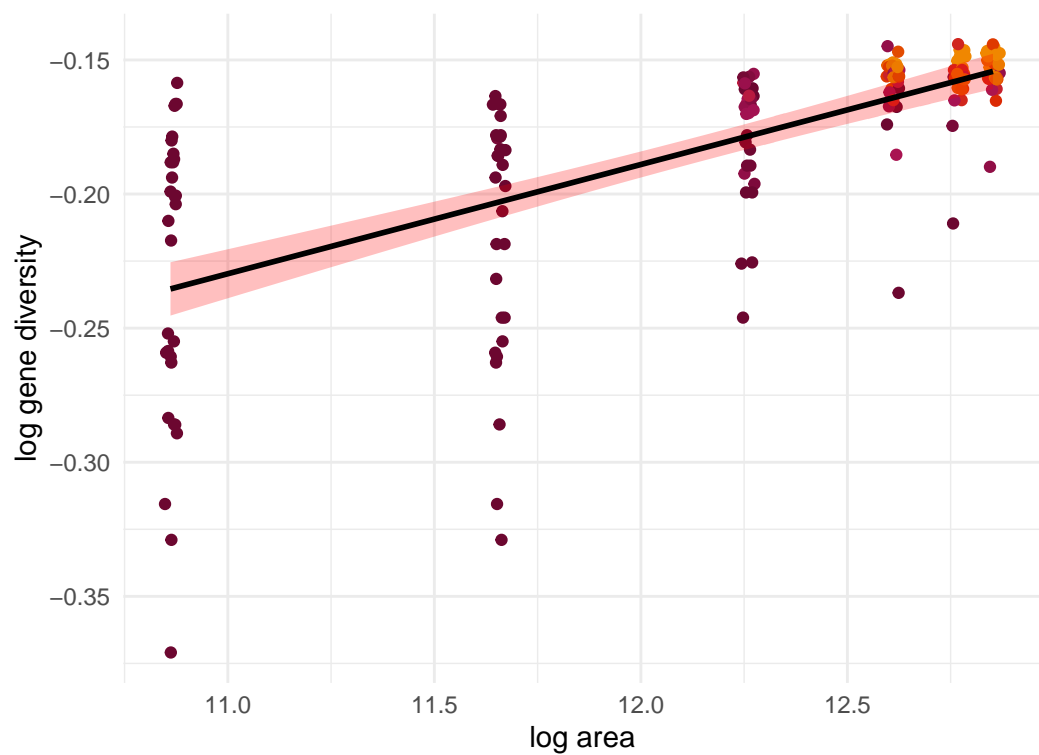
Geospiza fortis; $z=0.009$



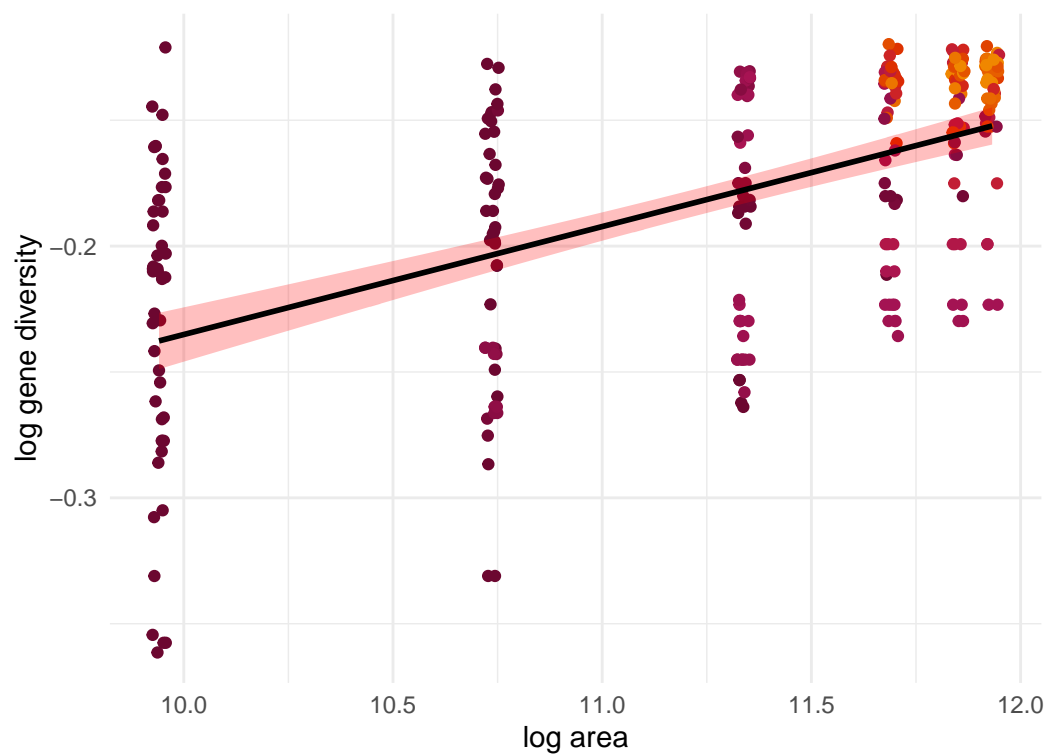
Geospiza fuliginosa; $z=0.006$



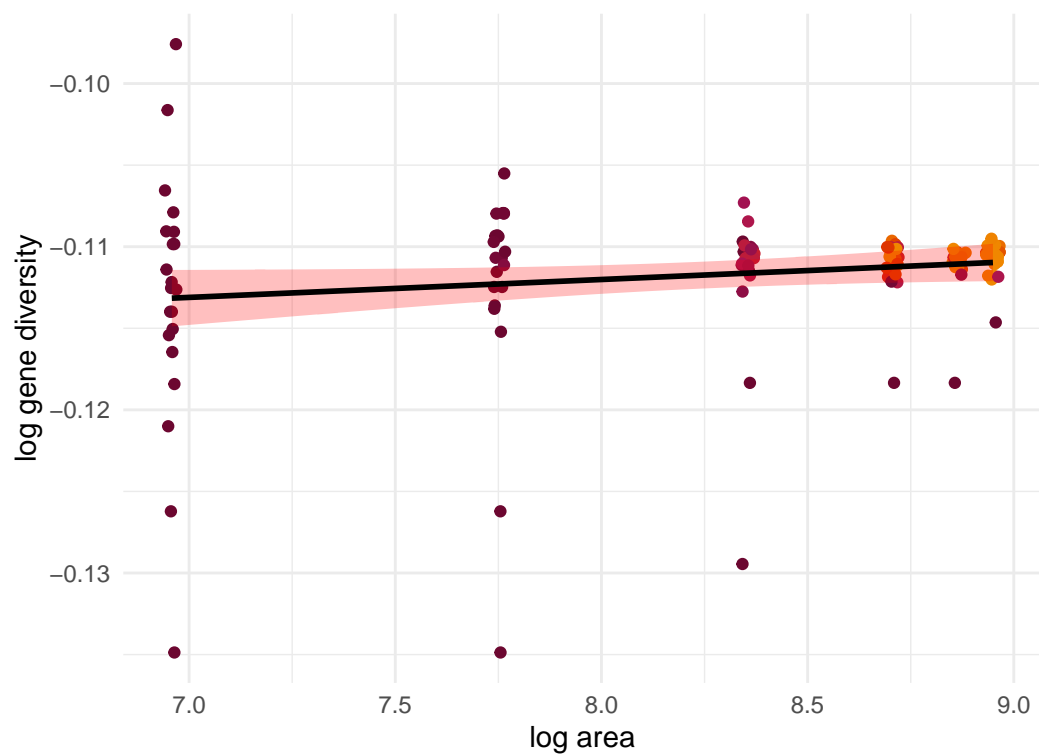
Meles meles; $z=0.041$



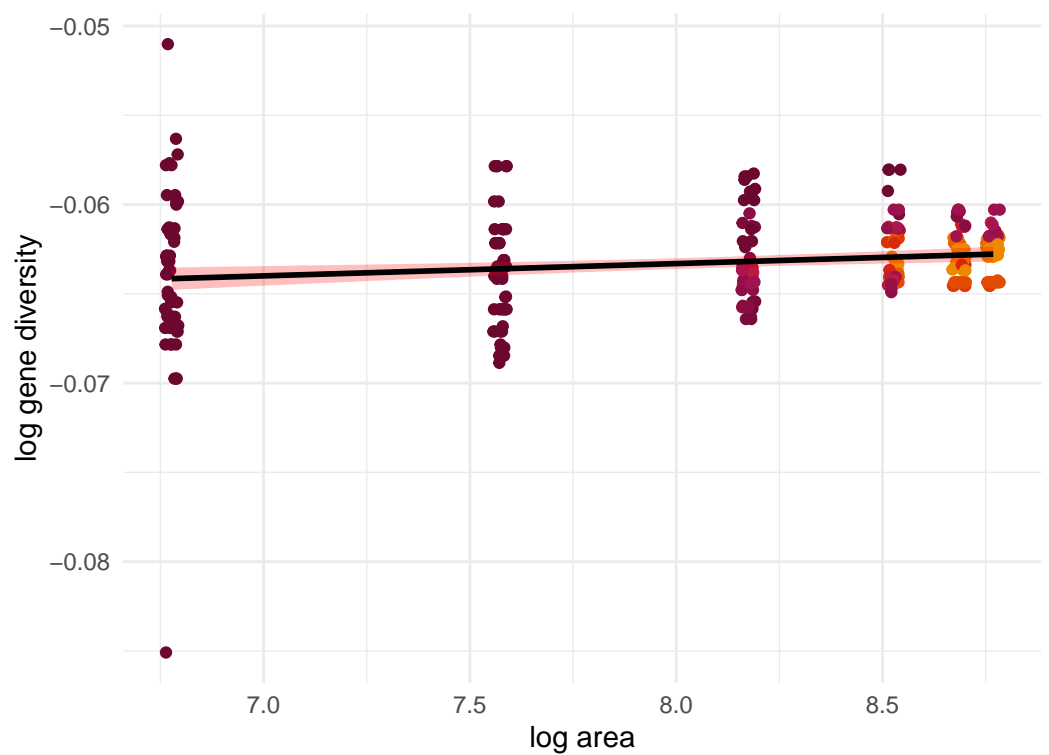
Gopherus polyphemus; $z=0.043$



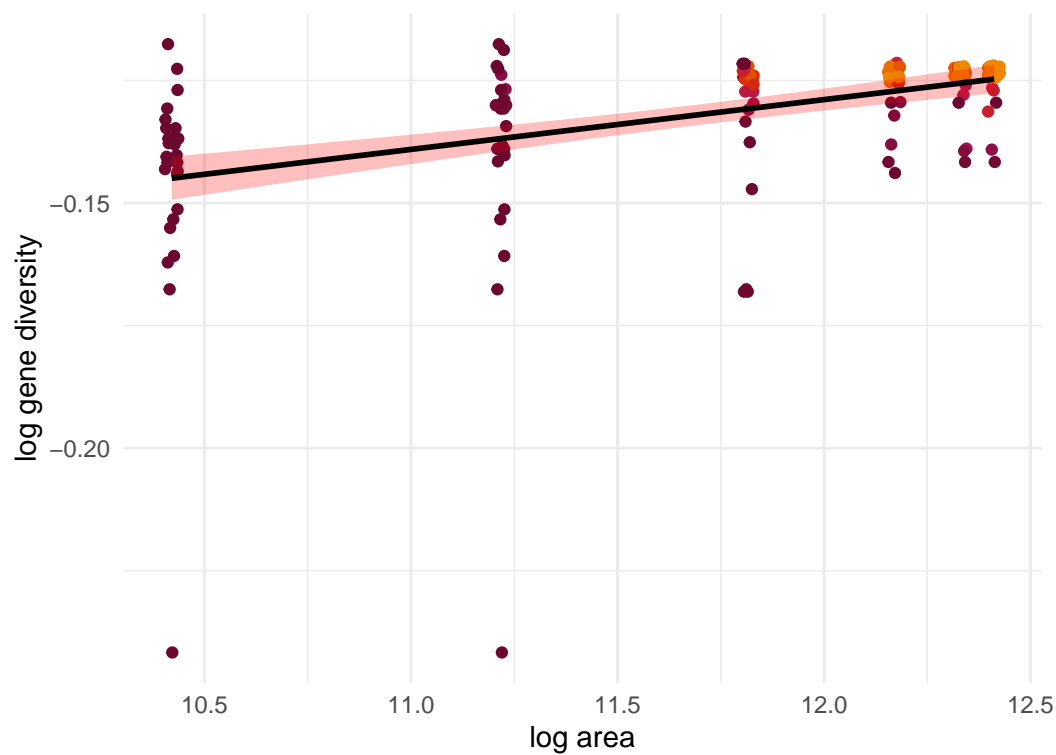
Geospiza fuliginosa; $z=NA$



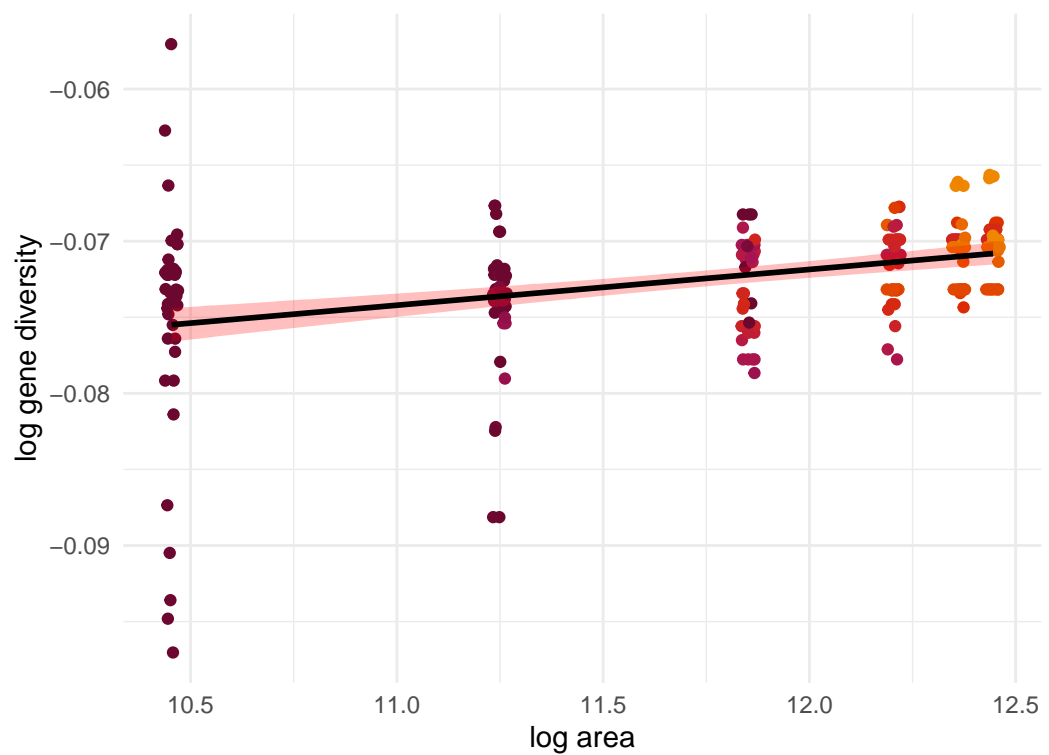
Microtus arvalis; $z=0.001$



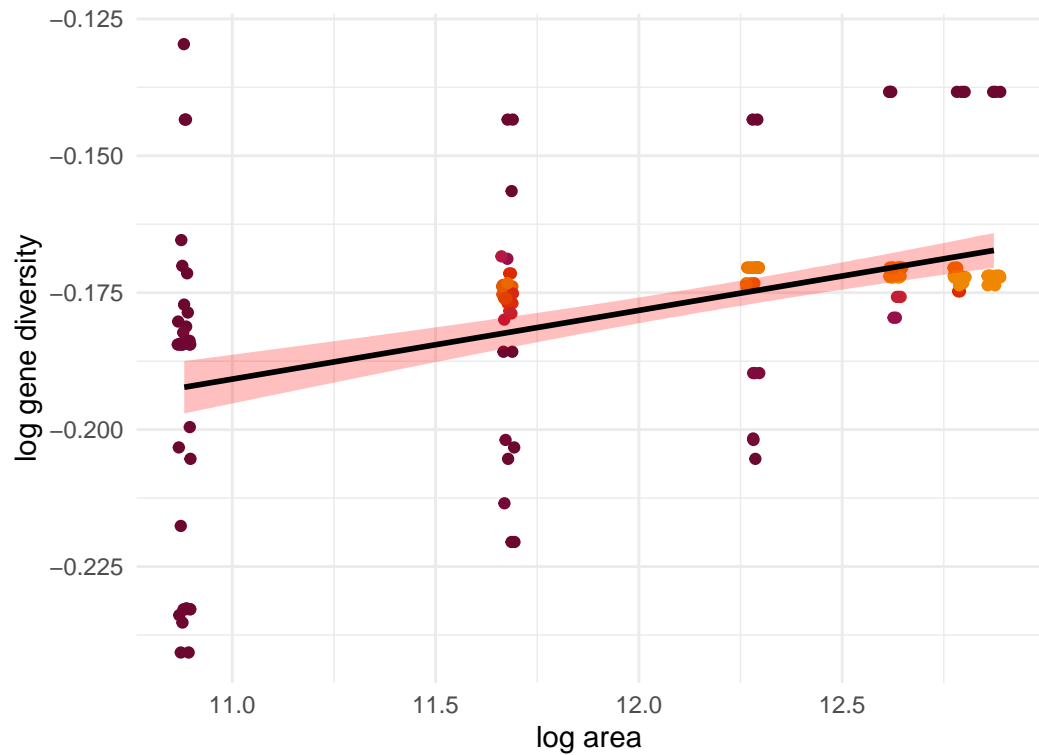
Aphelocoma californica; $z=0.01$



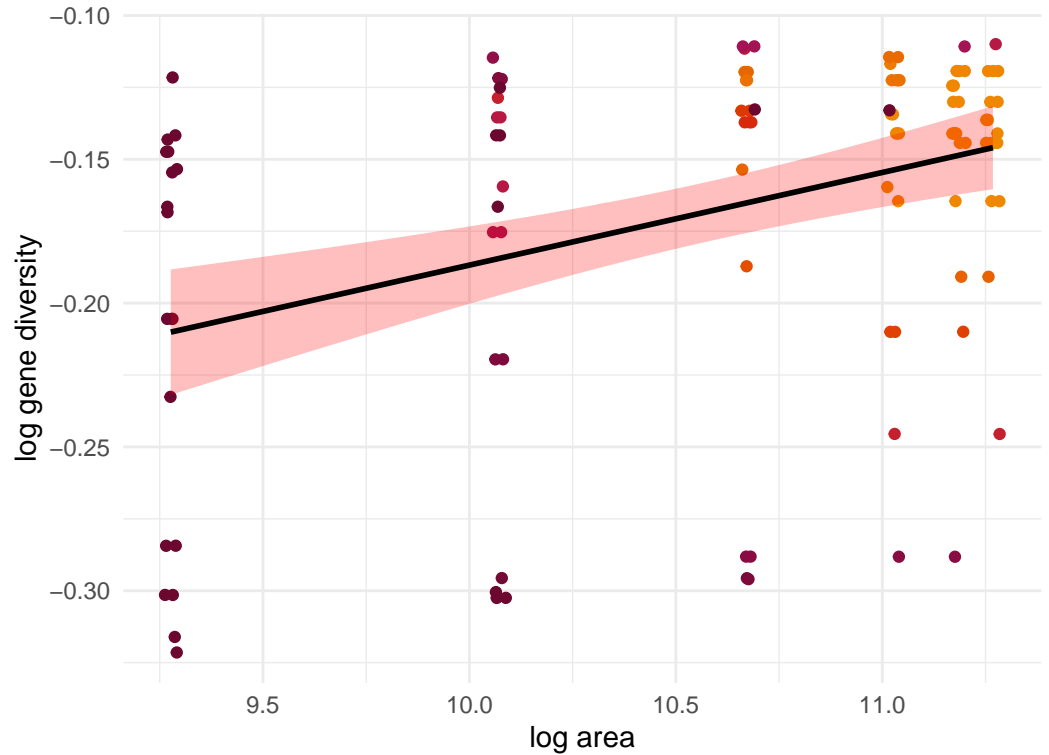
Canis latrans; $z=0.002$



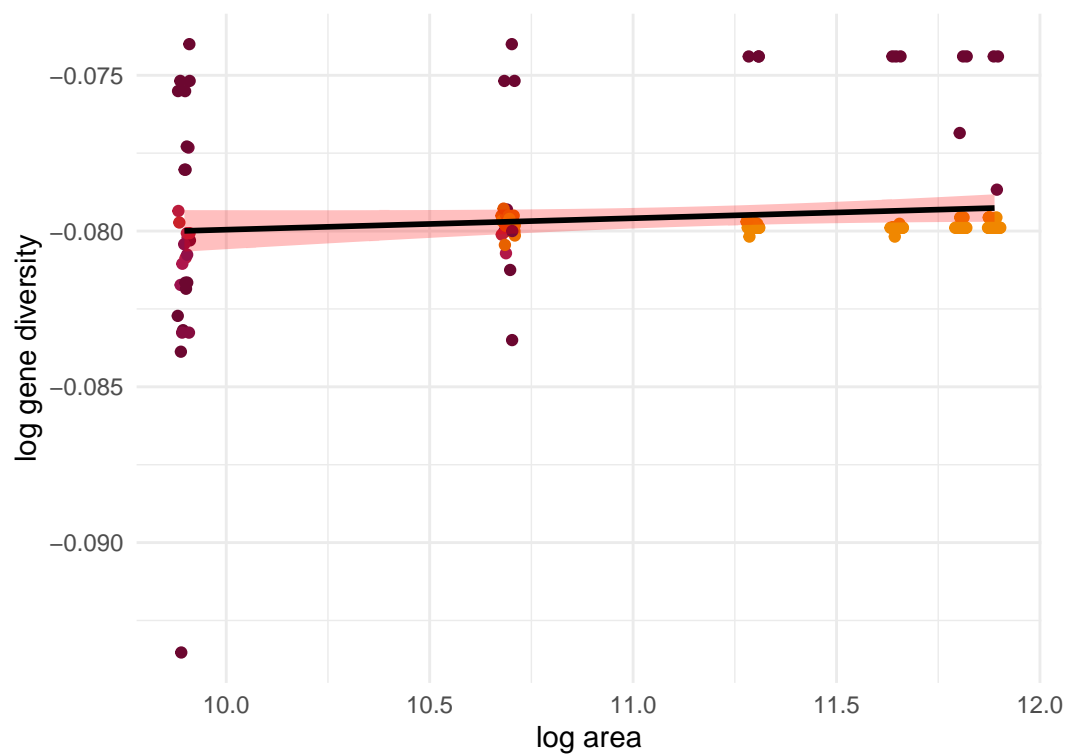
Rousettus aegyptiacus; $z=0.013$



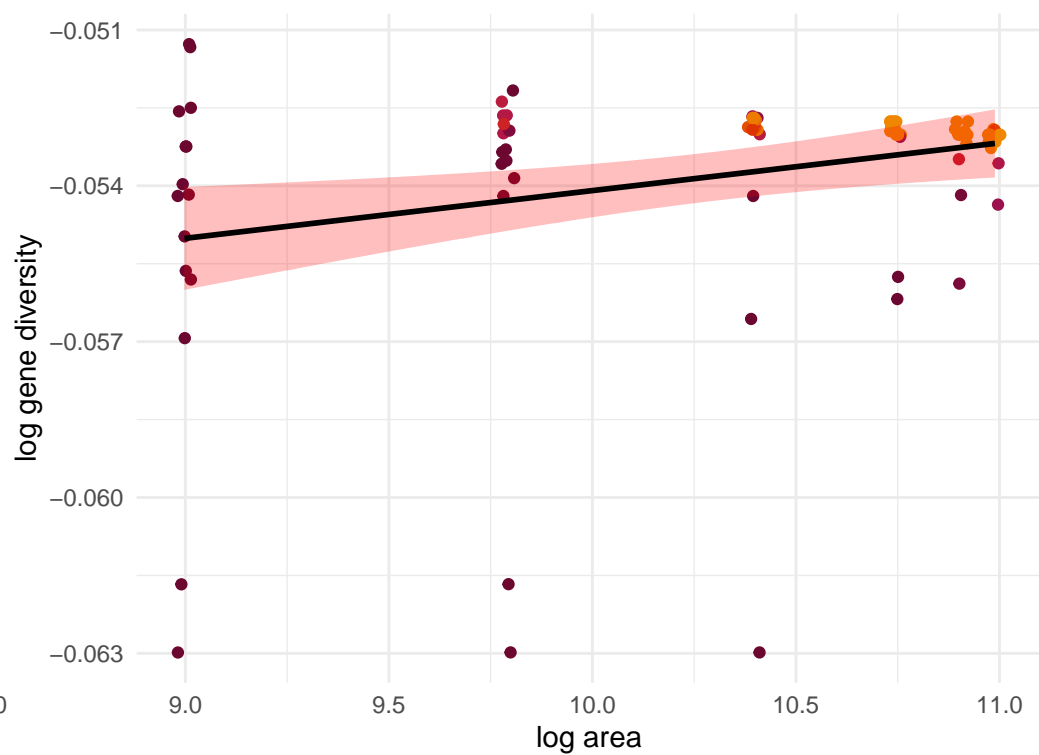
Ambystoma maculatum; $z=0.032$



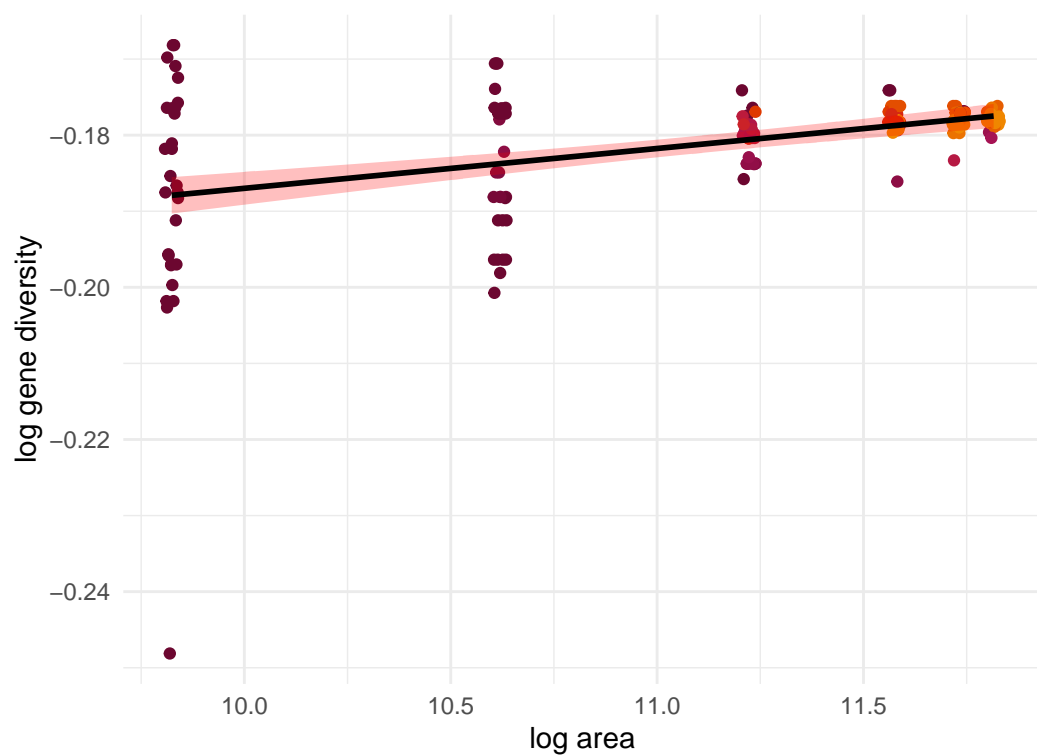
Myotis lucifugus; z=NA



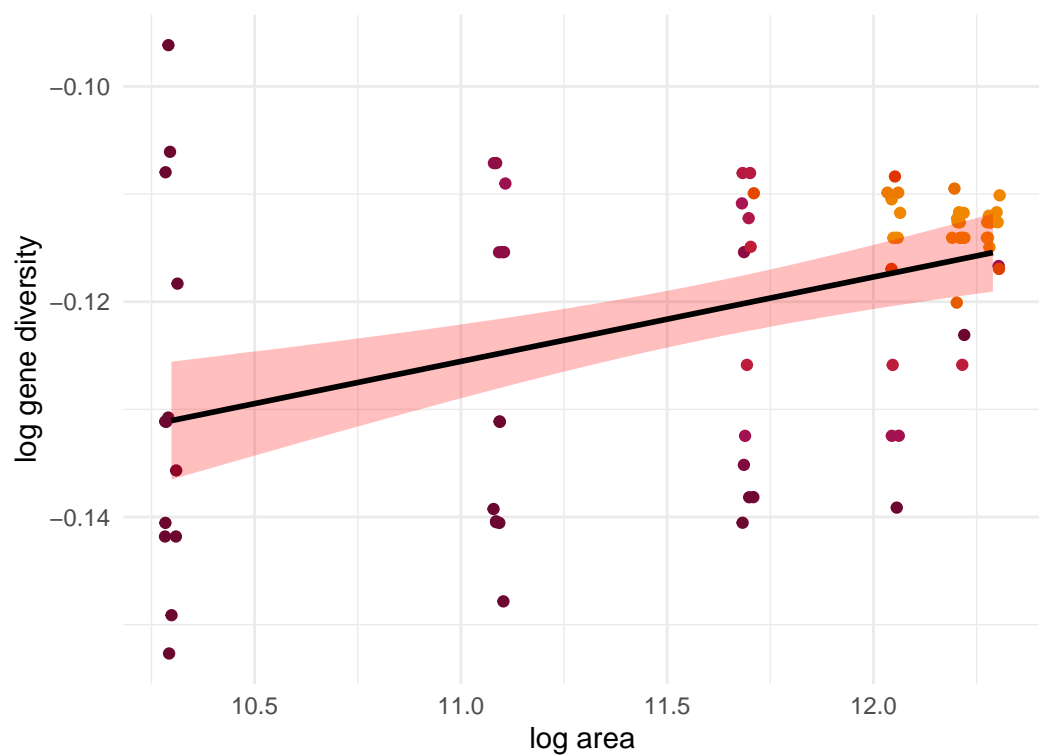
Myotis septentrionalis; z=0.001



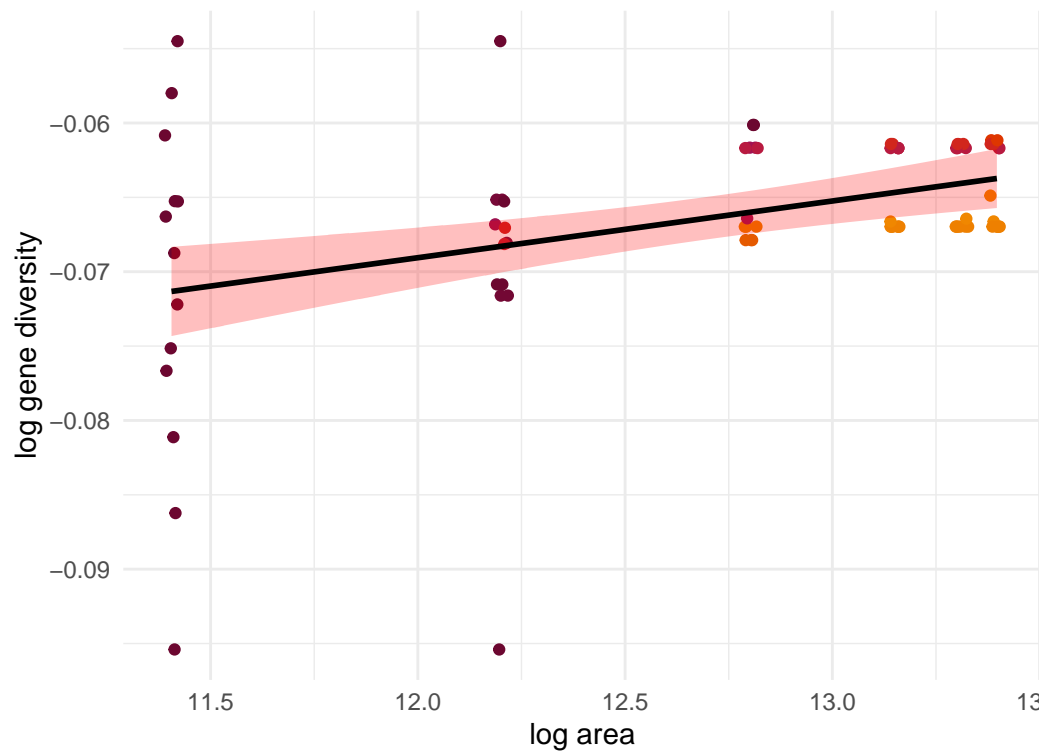
Martes americana; z=0.005



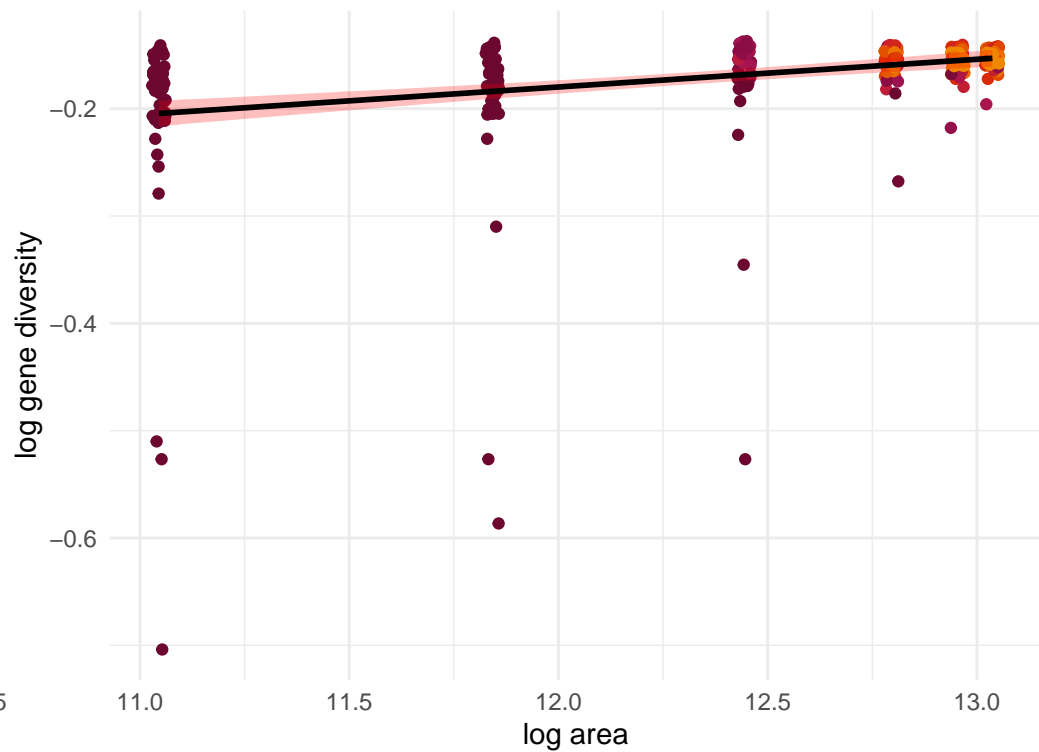
Lemmus lemmus; z=0.008



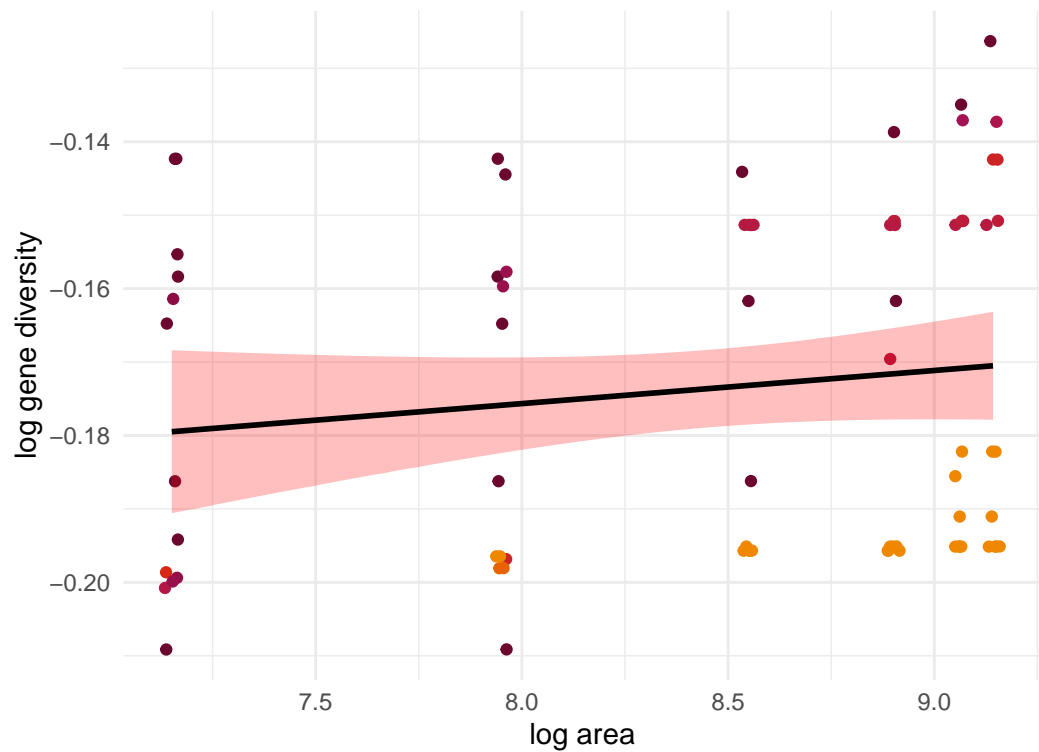
Poecile hudsonicus; $z=0.004$



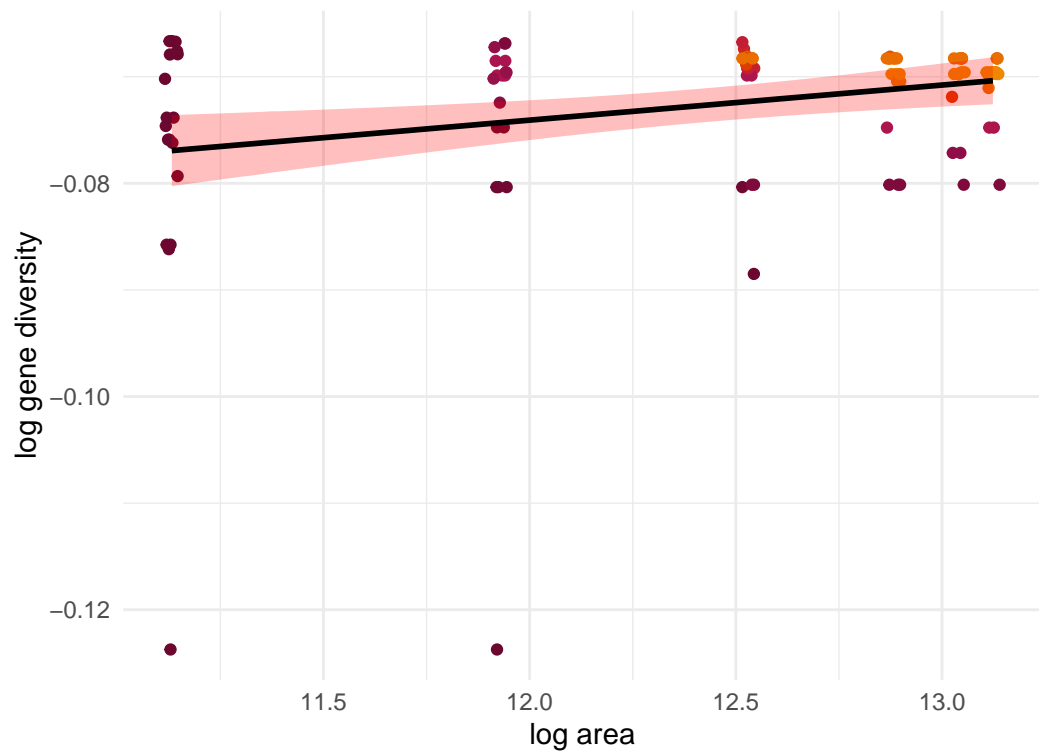
Odocoileus hemionus; $z=0.026$



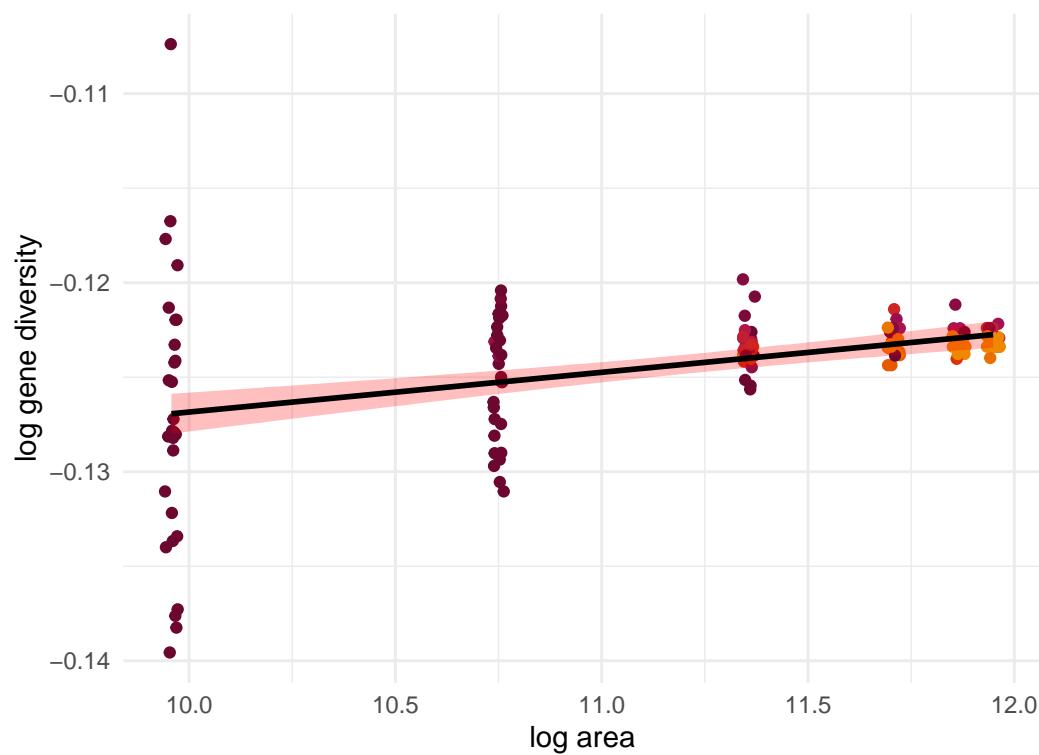
Amblyrhynchus cristatus; $z=NA$



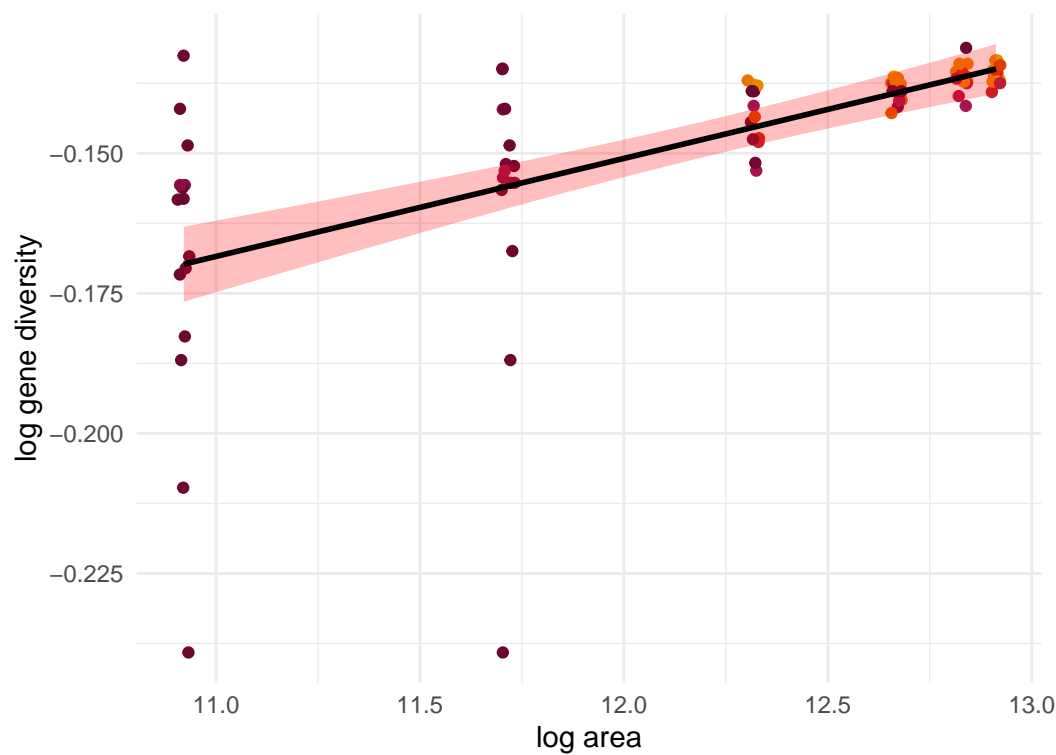
Rangifer tarandus; $z=0.003$



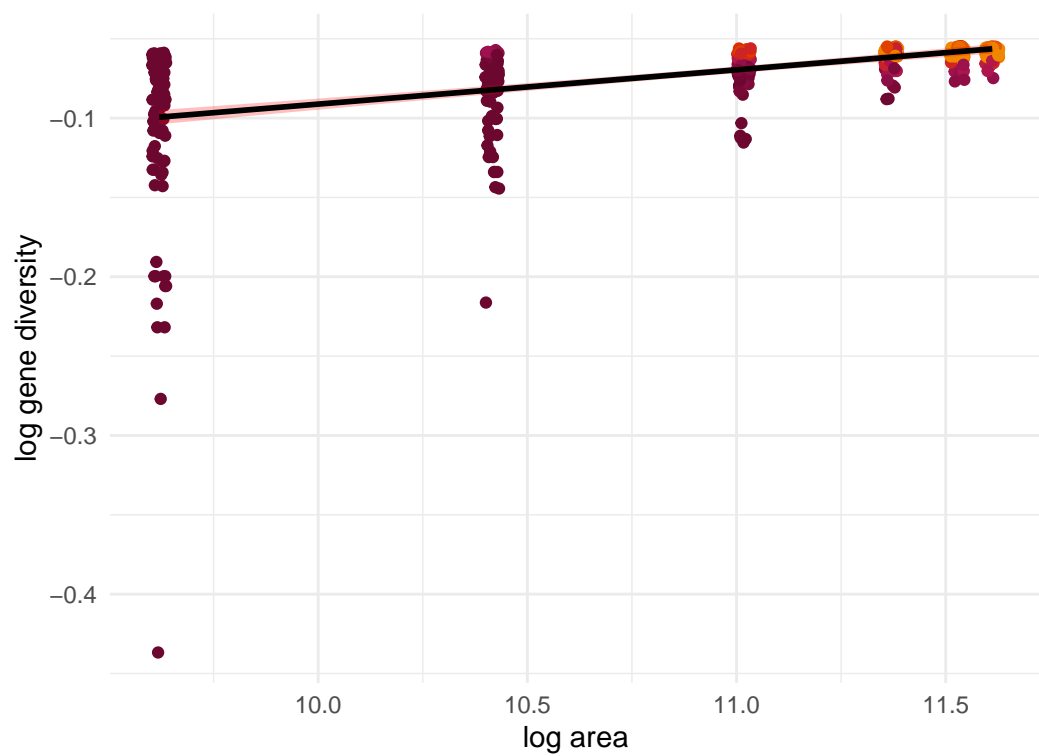
Lynx canadensis; $z=0.002$



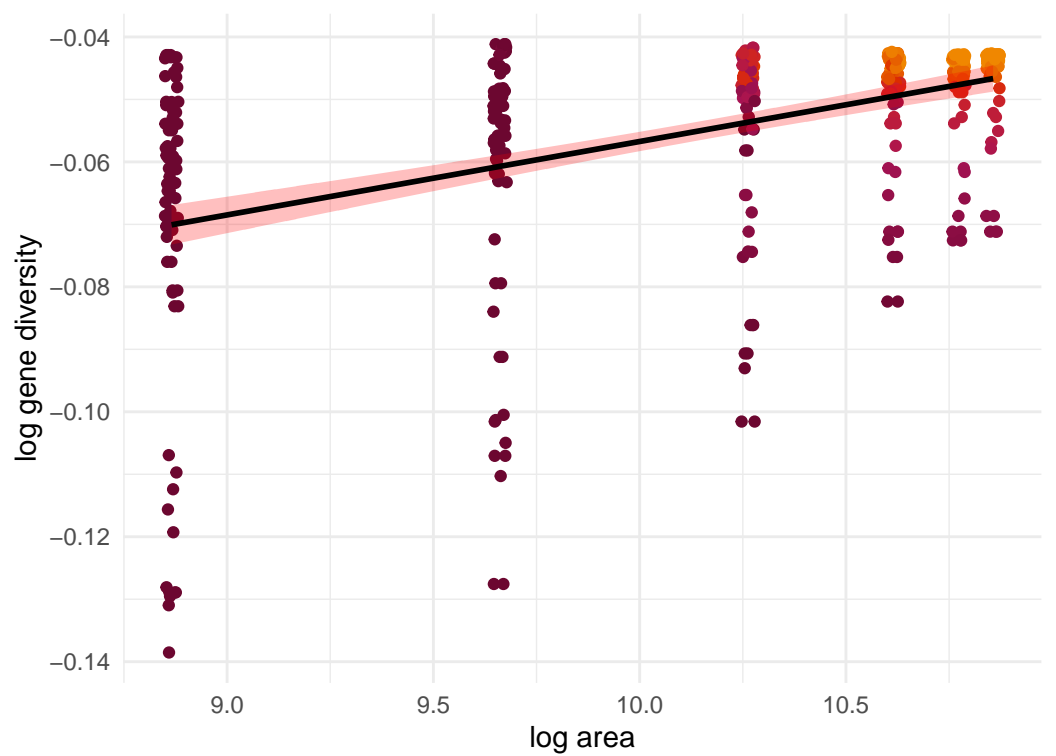
Felis silvestris; $z=0.017$



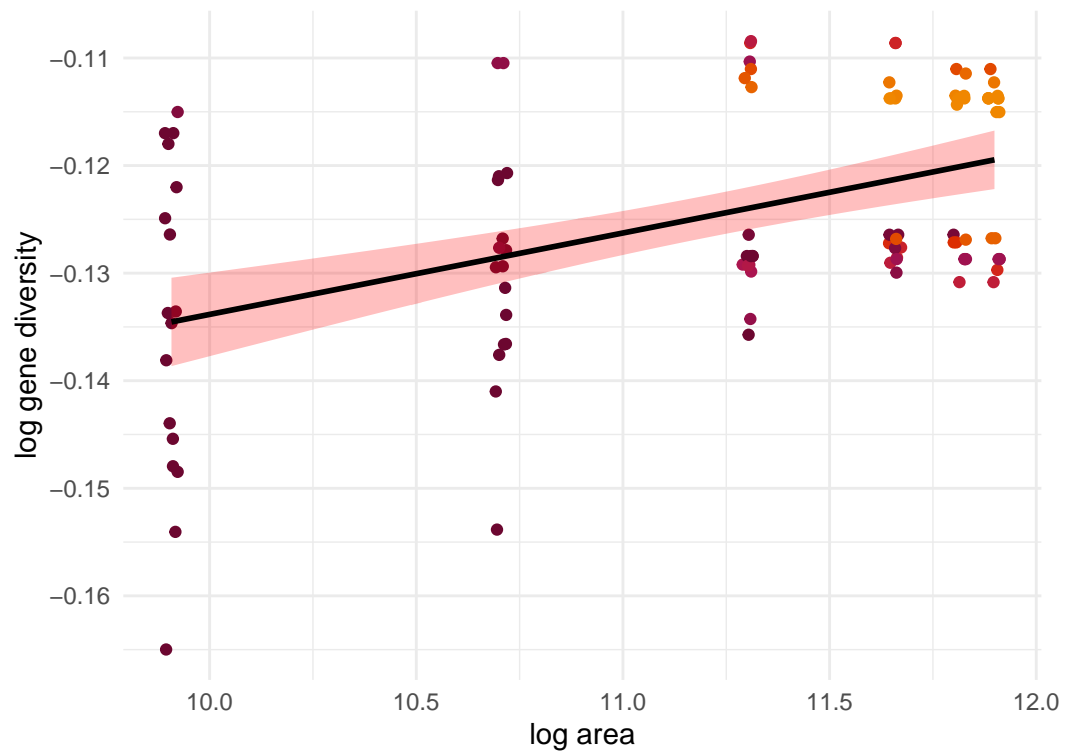
Ascapus montanus; $z=0.022$



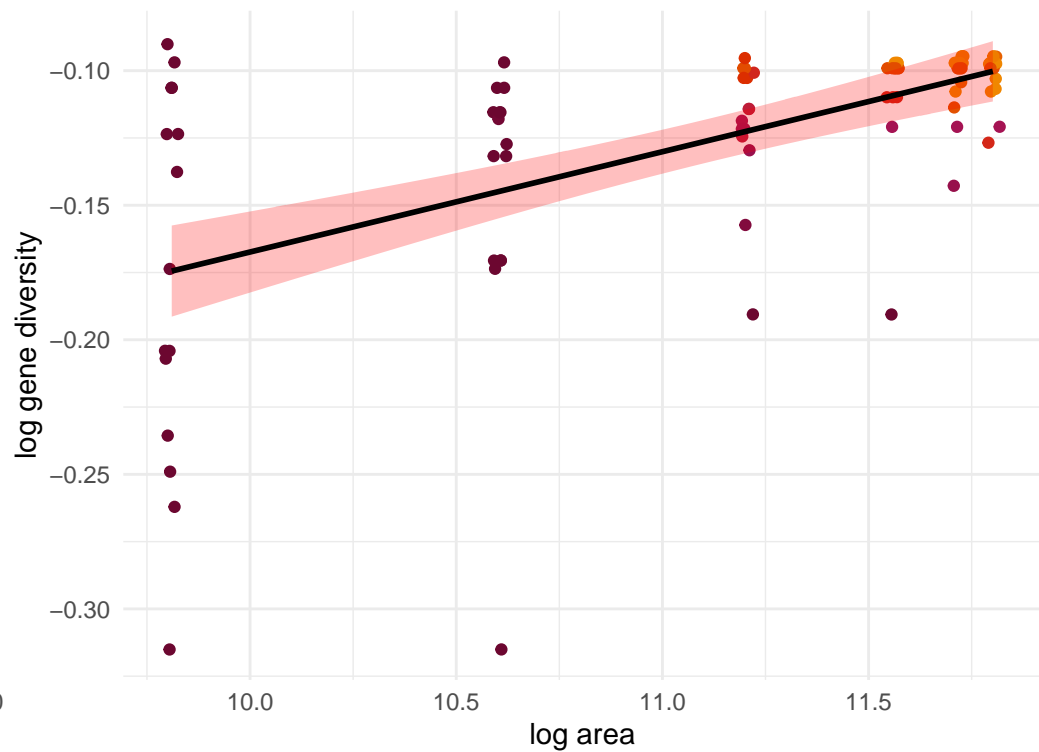
Ambystoma barbouri; $z=0.012$



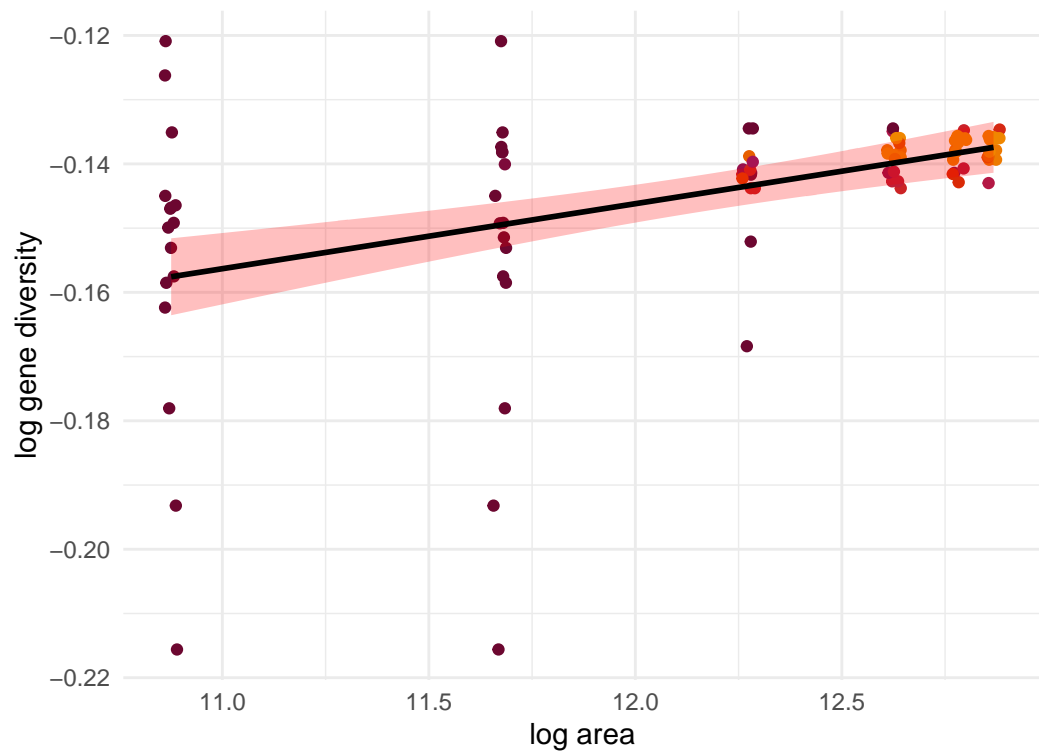
Strix occidentalis; $z=0.008$



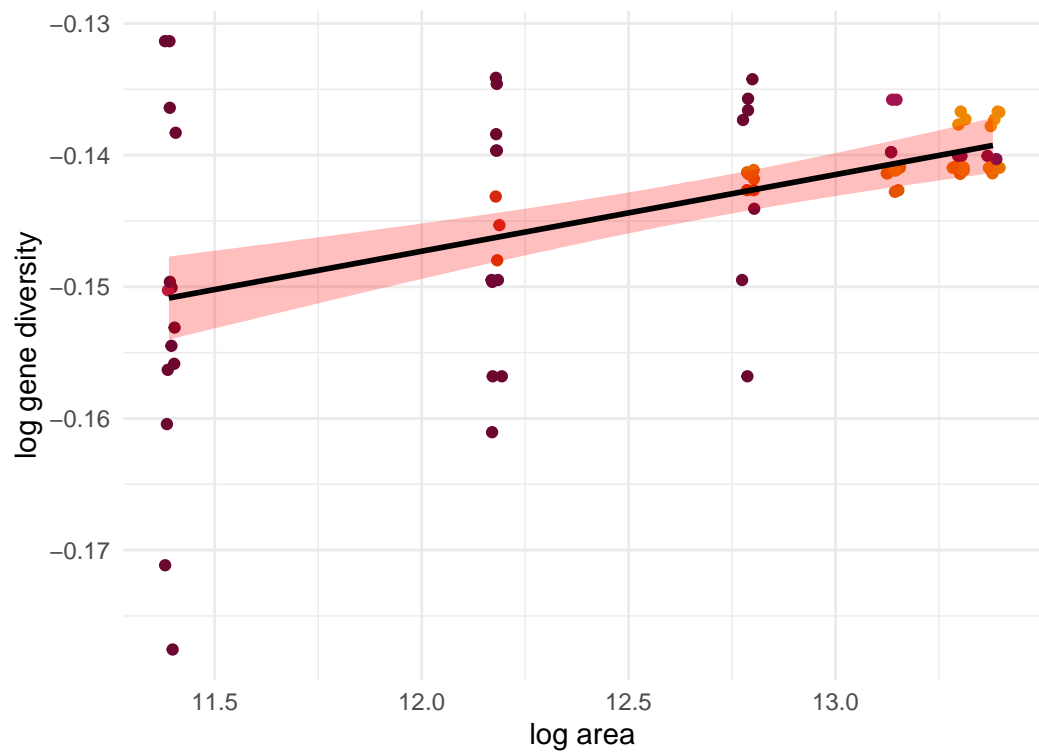
Liolaemus tenuis; $z=0.037$



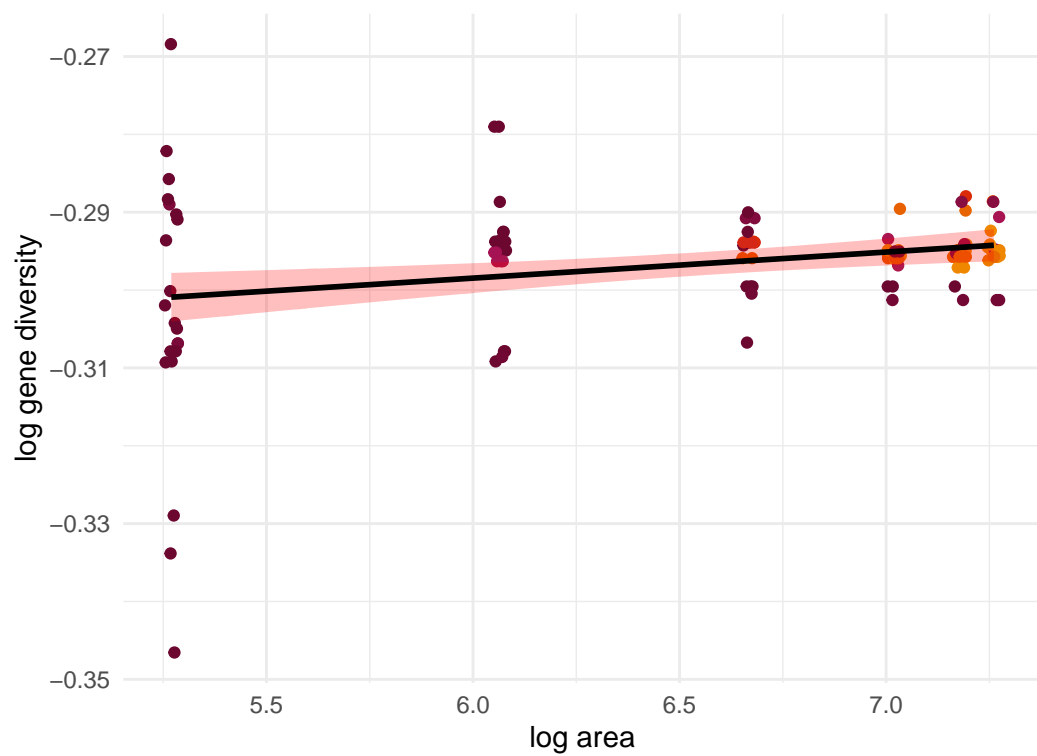
Alces alces; $z=0.01$



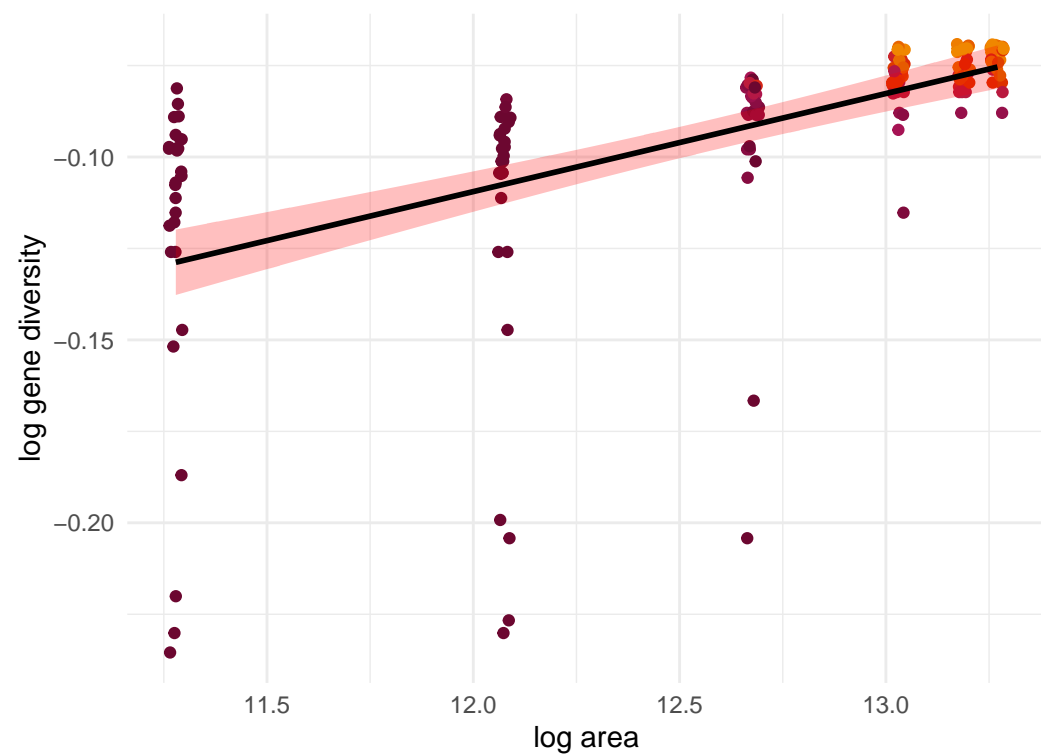
Ursus maritimus; $z=0.006$



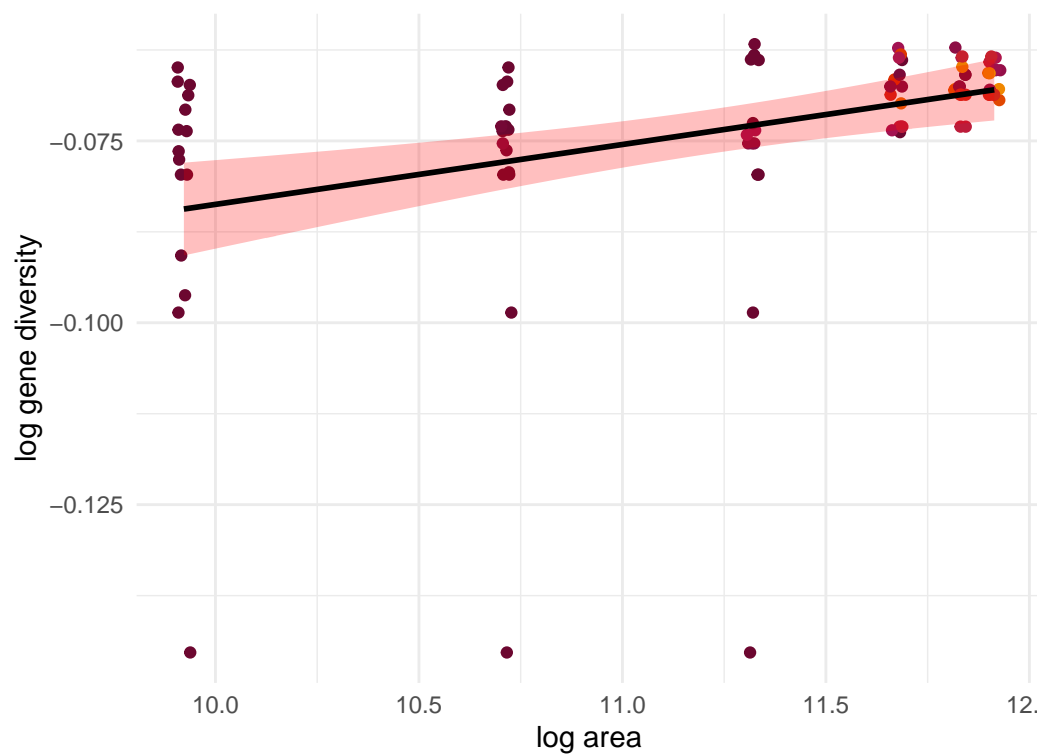
Plethodon albagula; $z=0.003$



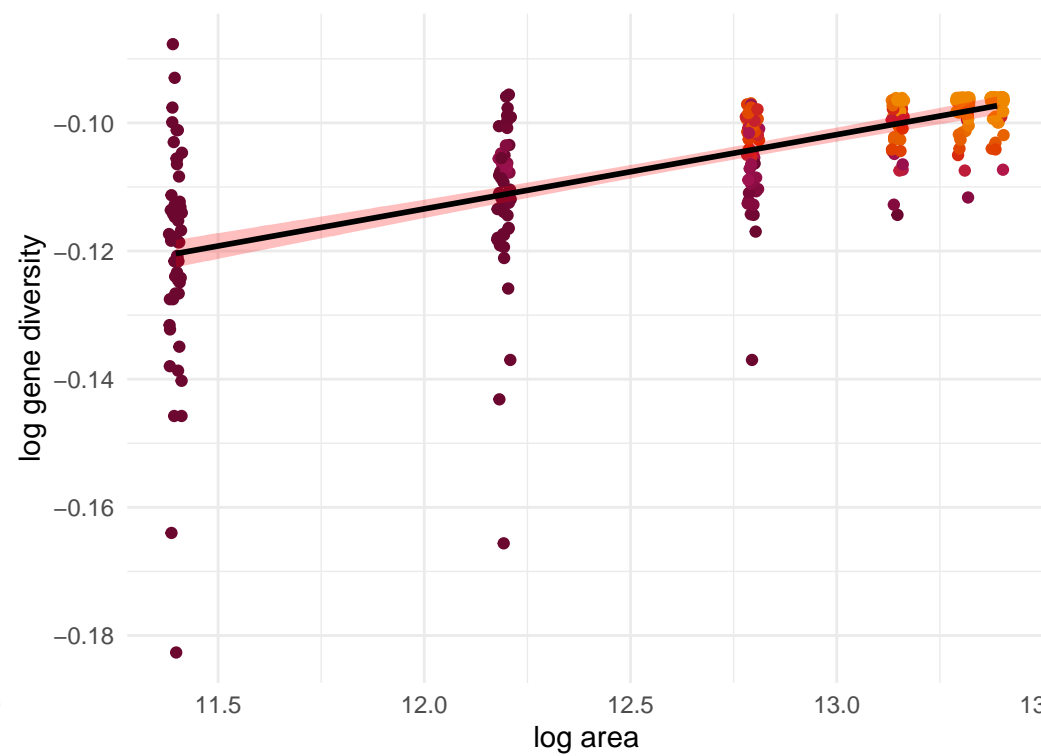
Ursus americanus; $z=0.027$



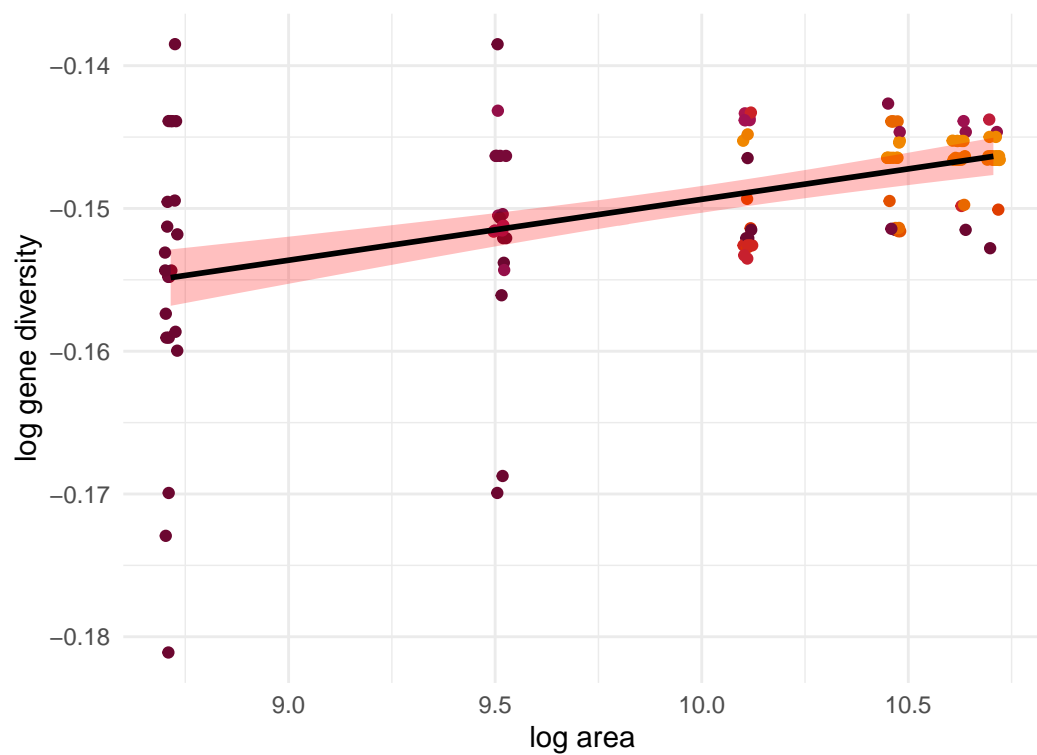
Myotis escaleraei; $z=0.008$



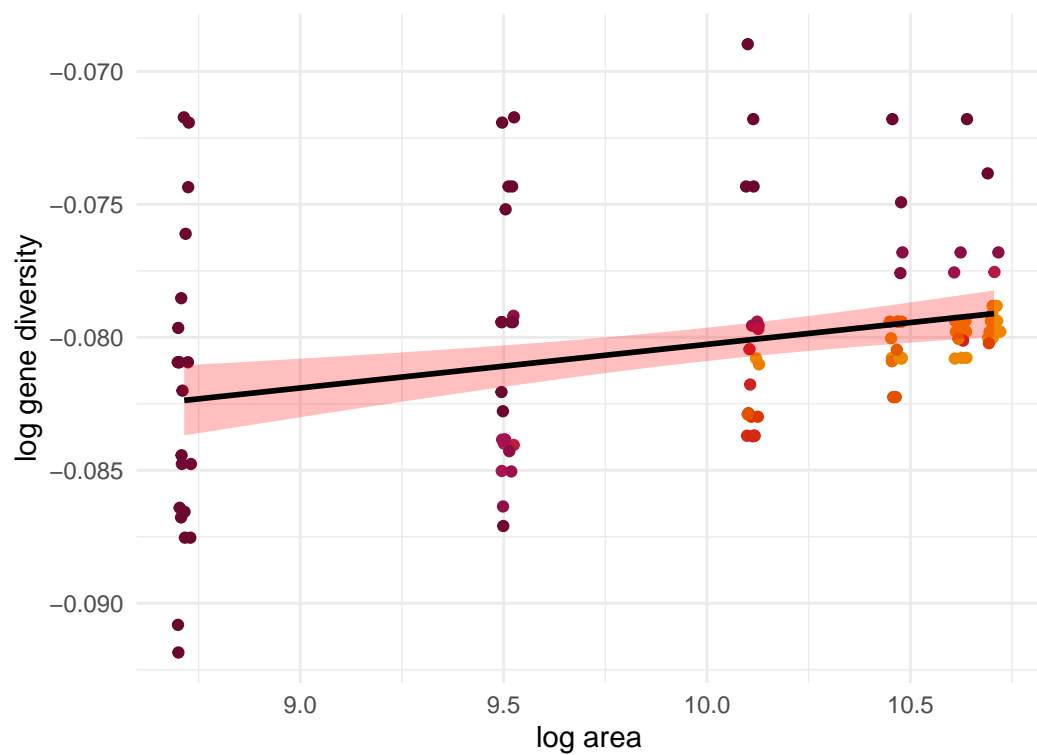
Lynx rufus; $z=0.012$



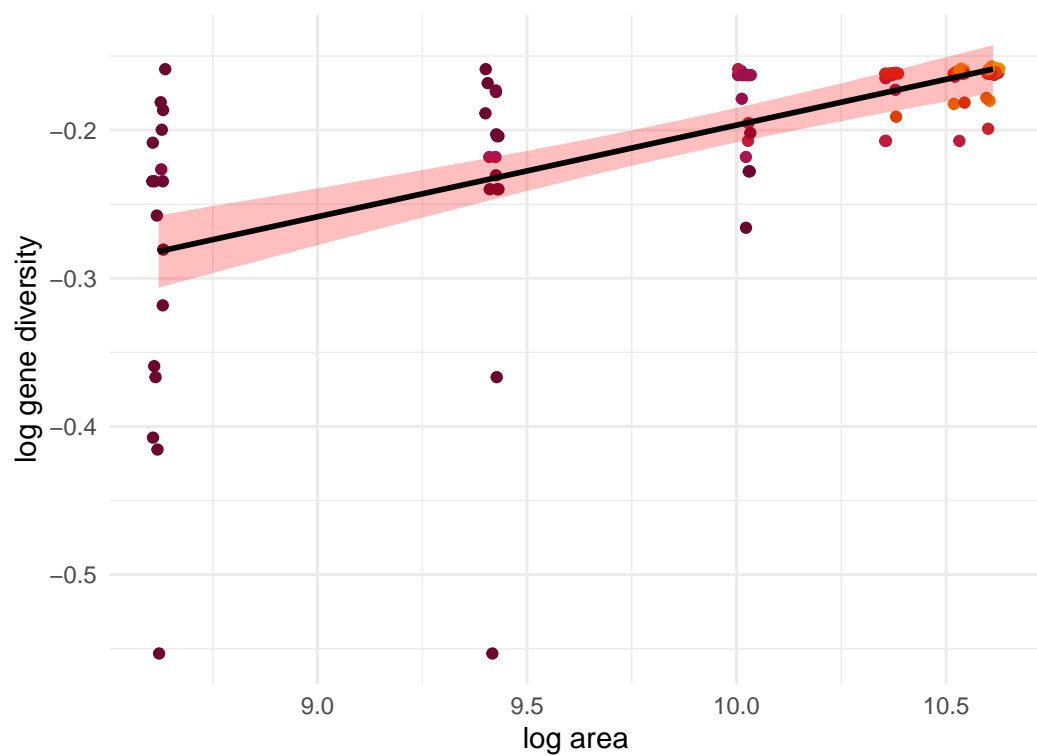
Ambystoma maculatum; $z=0.004$



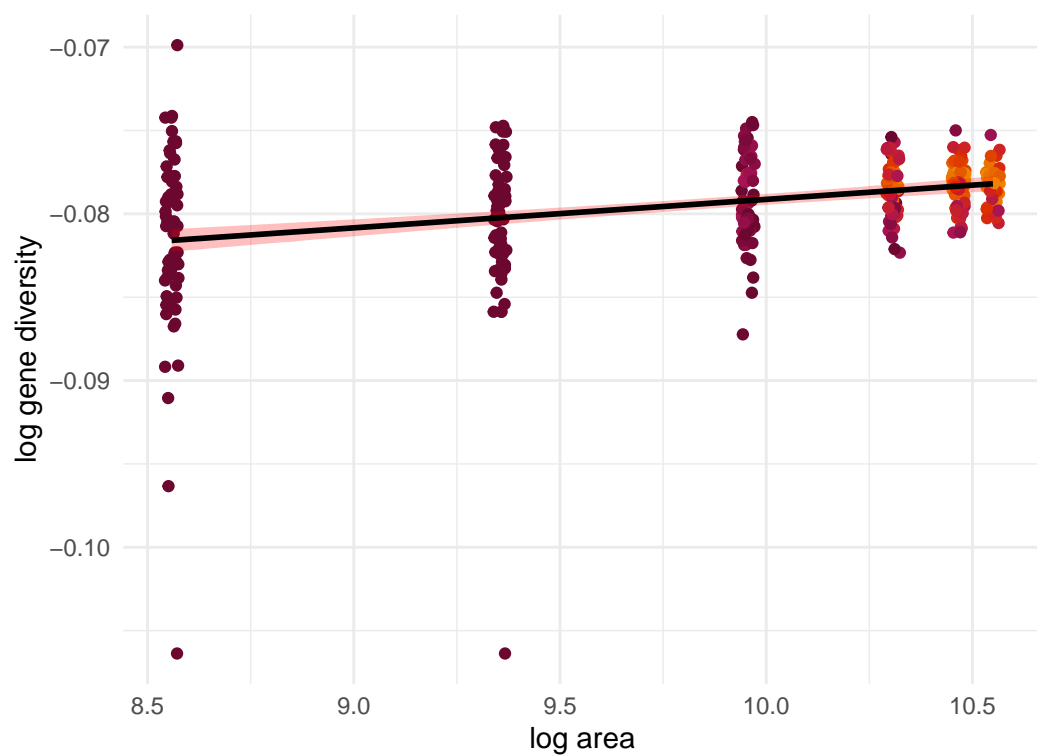
Rana sylvatica; $z=0.002$



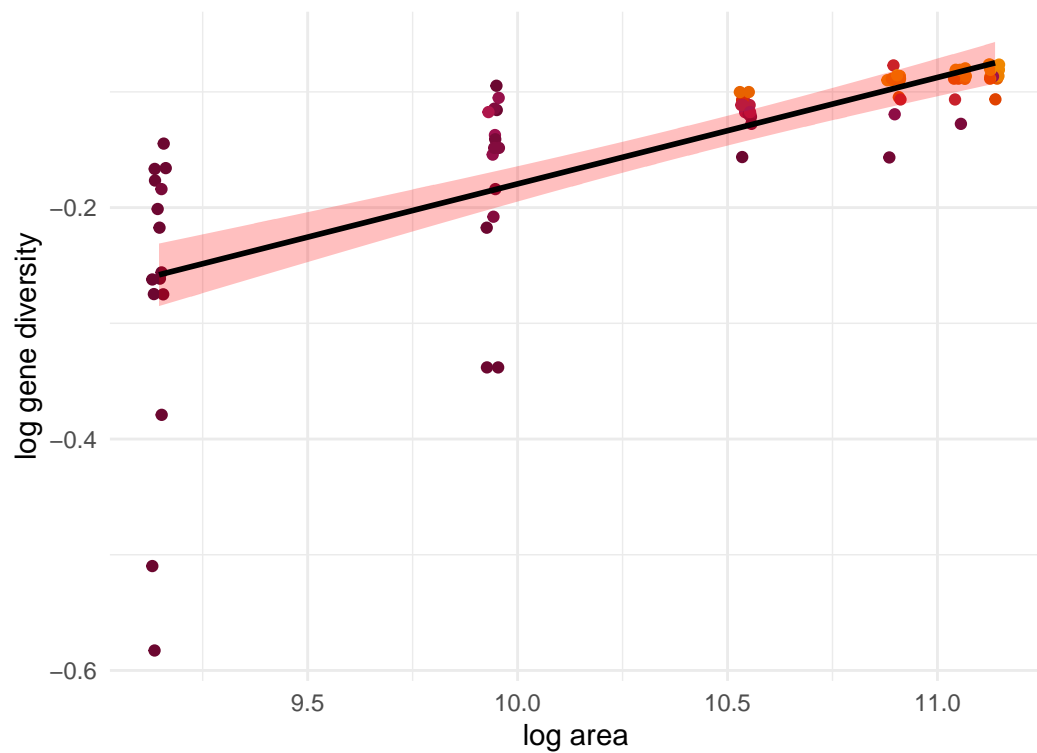
Rana draytonii; $z=0.062$



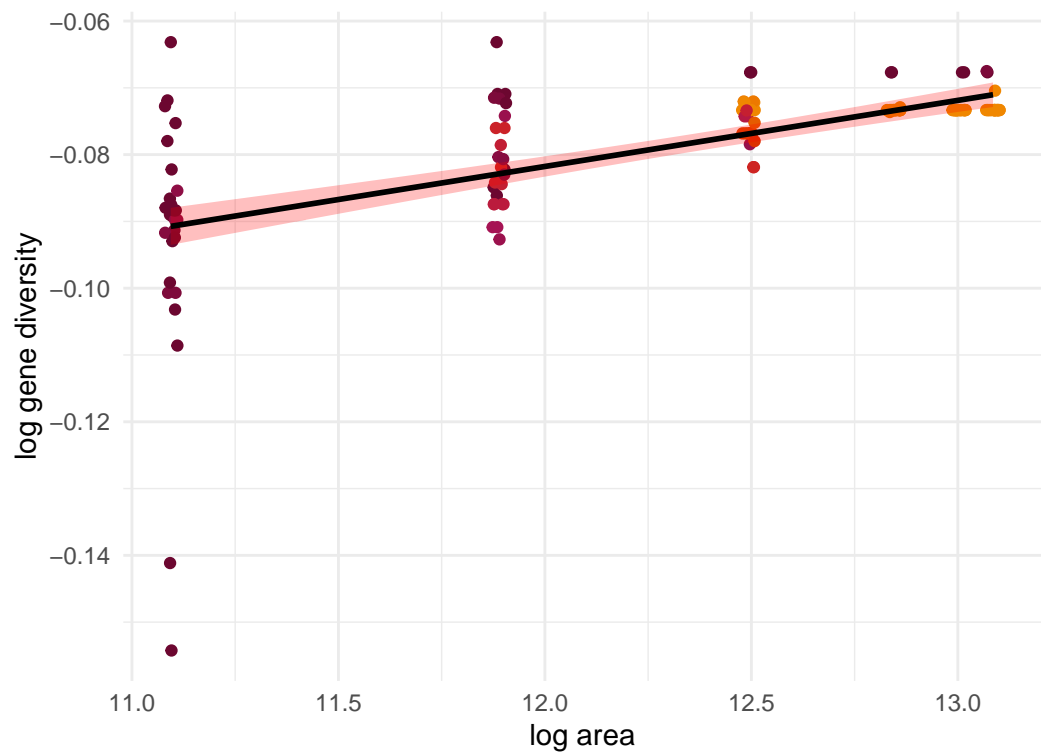
Odocoileus virginianus; $z=0.002$



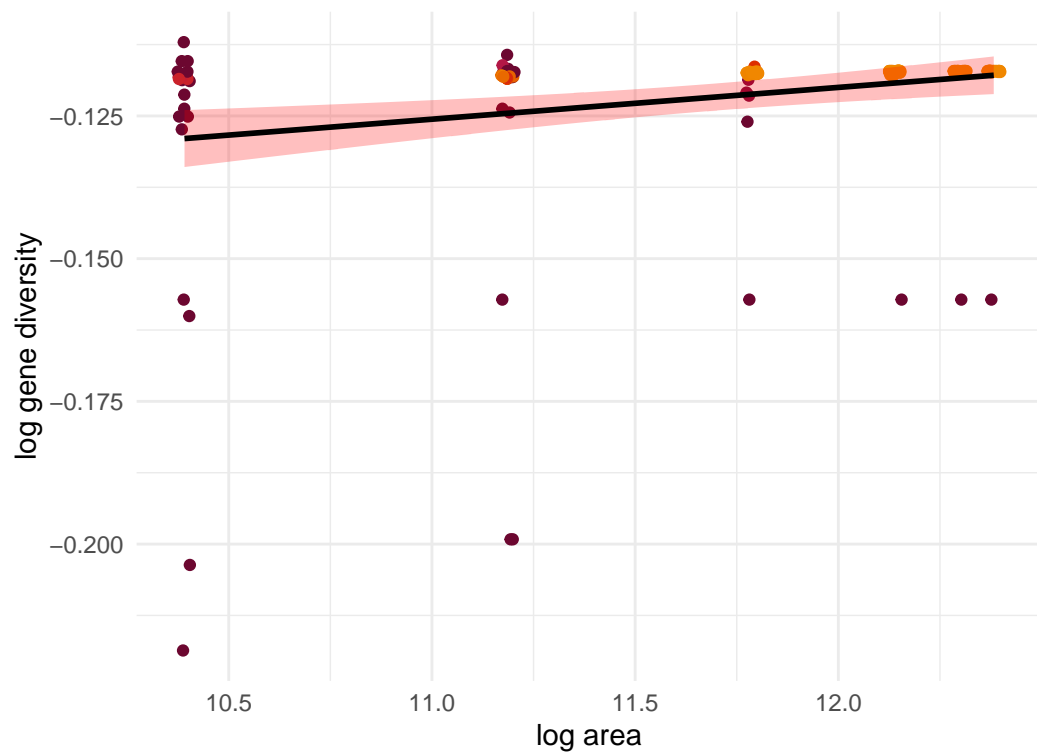
Hydromantes platycephalus; $z=0.092$



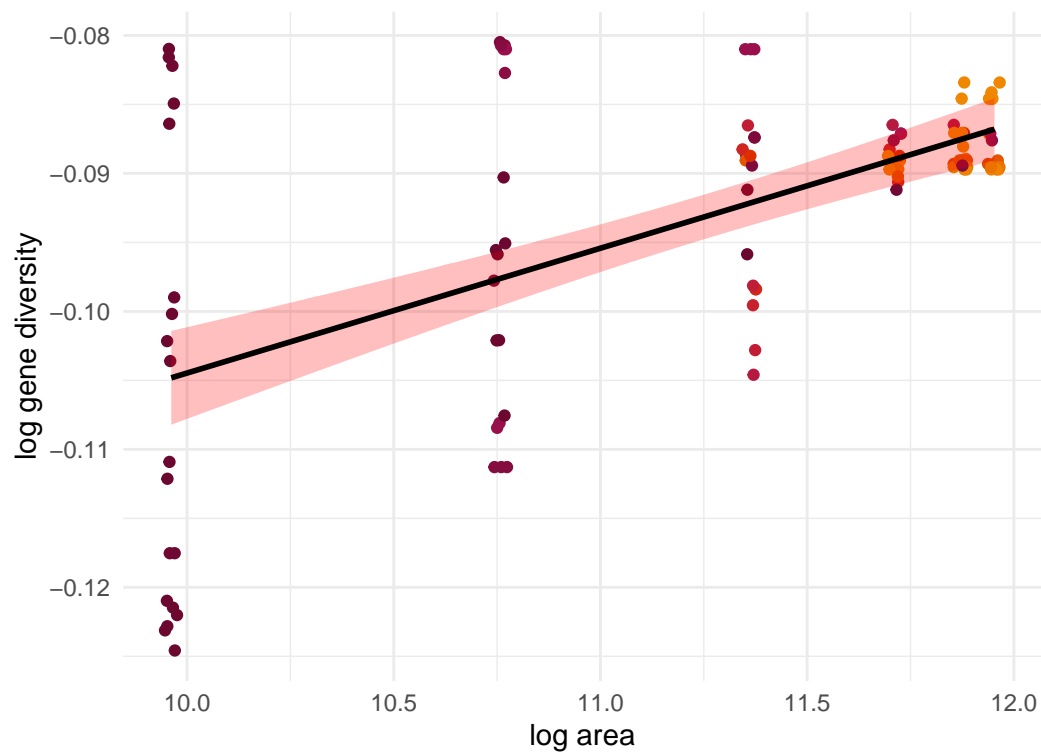
Rangifer tarandus; $z=0.01$



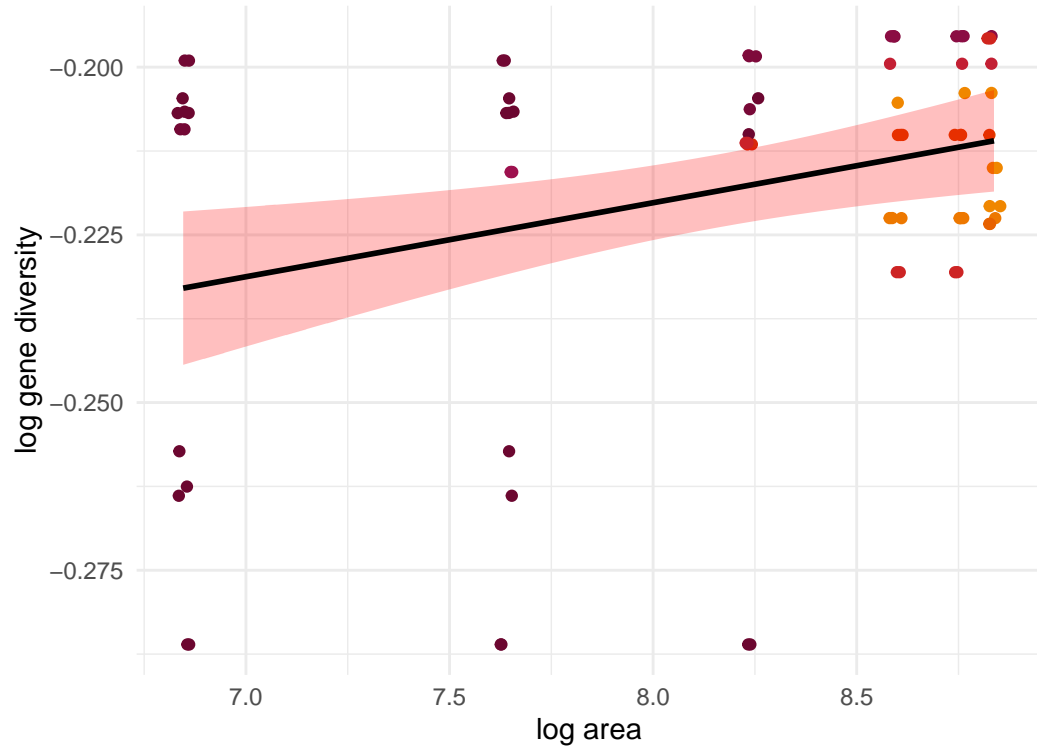
Rhinolophus ferrumequinum; $z=0.006$



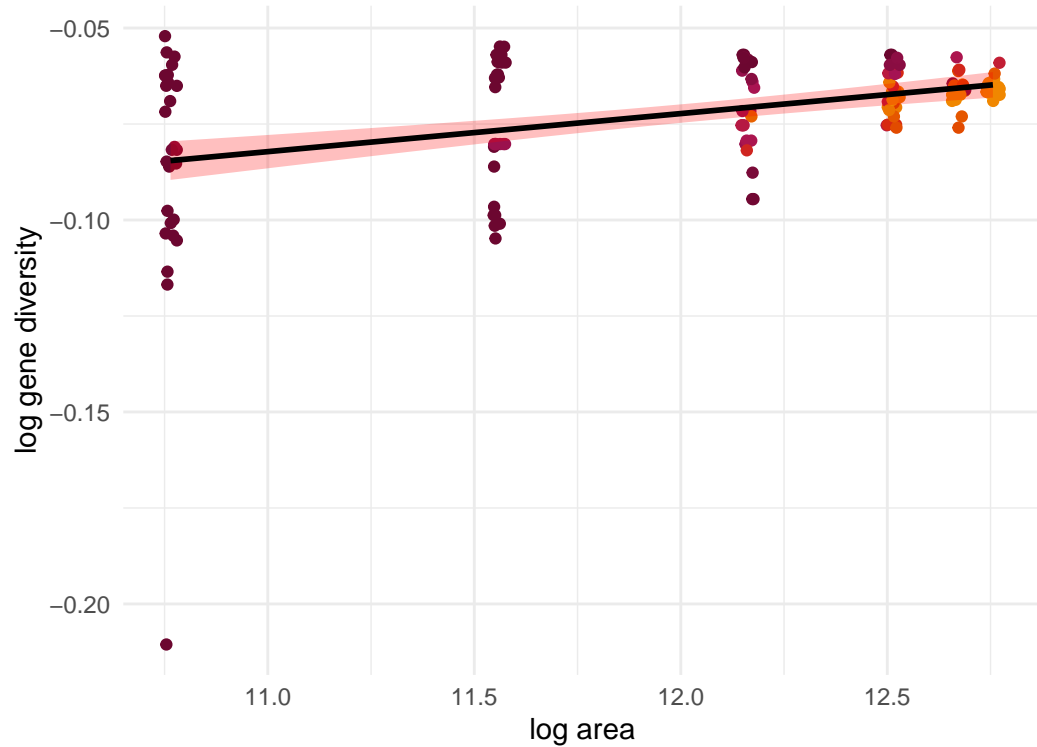
Dipsosaurus dorsalis; $z=0.009$



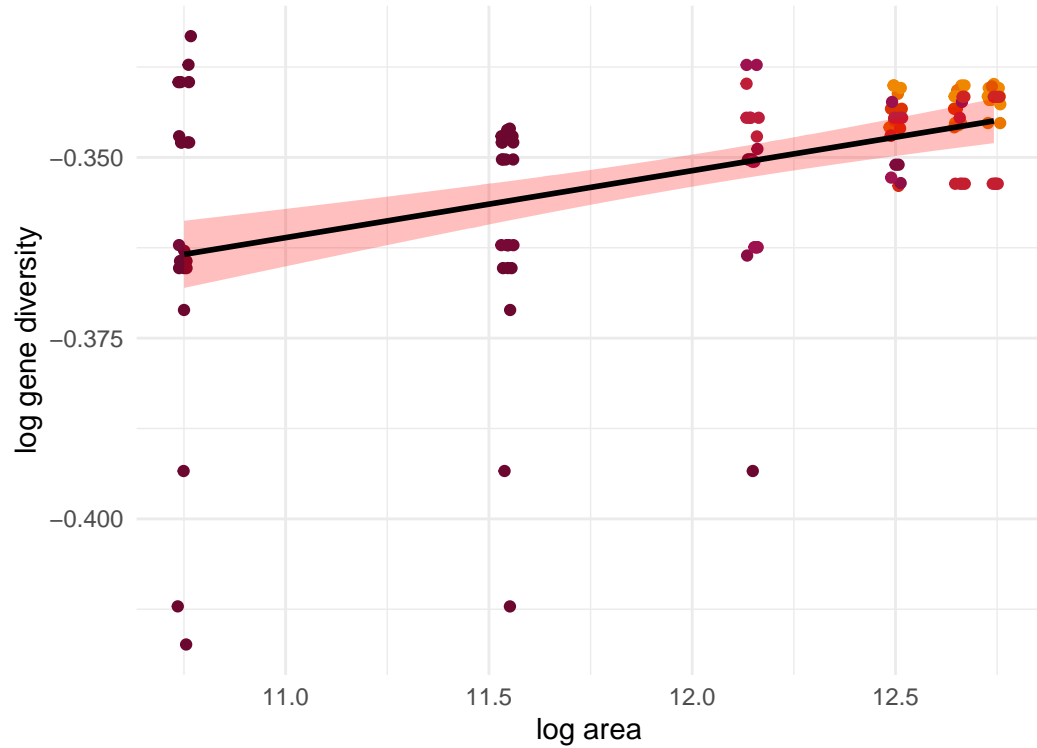
Uma inornata; $z=0.011$



Rangifer tarandus; $z=0.01$



Miniopterus schreibersii; $z=0.009$



Sorex antinorii; $z=0.01$

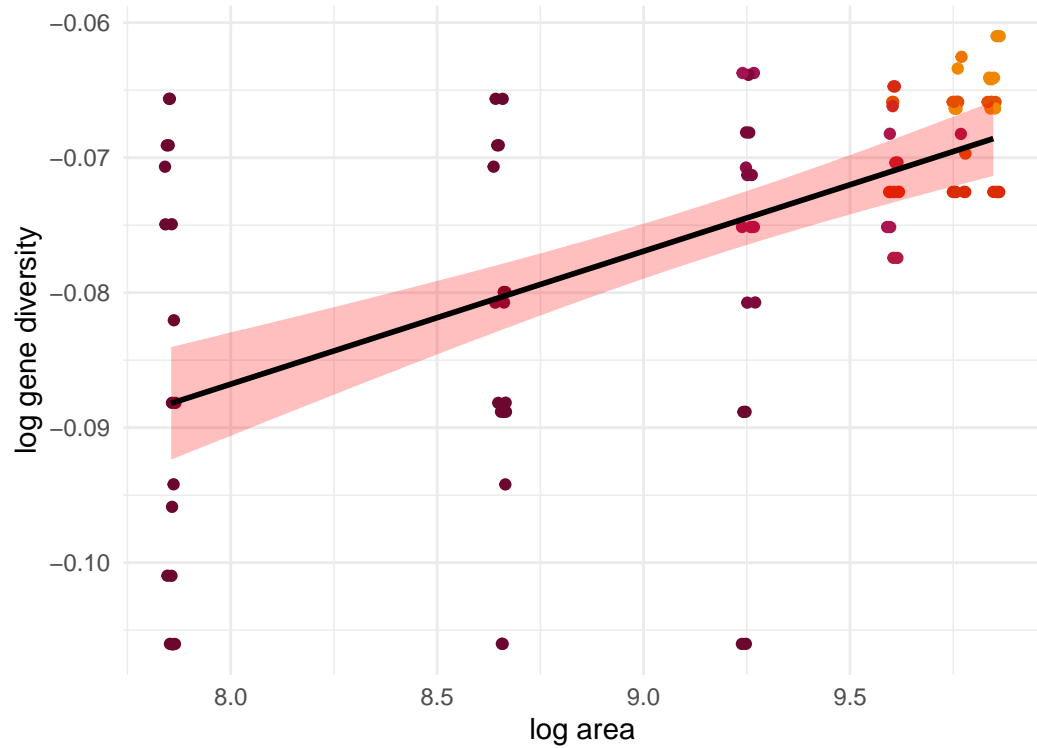


Figure S3. Comparison of F_{ST} values from the data analyzed here versus mean F_{ST} estimates per species within the mammal MacroPopGen dataset. The red dashed line indicates a perfect correlation.

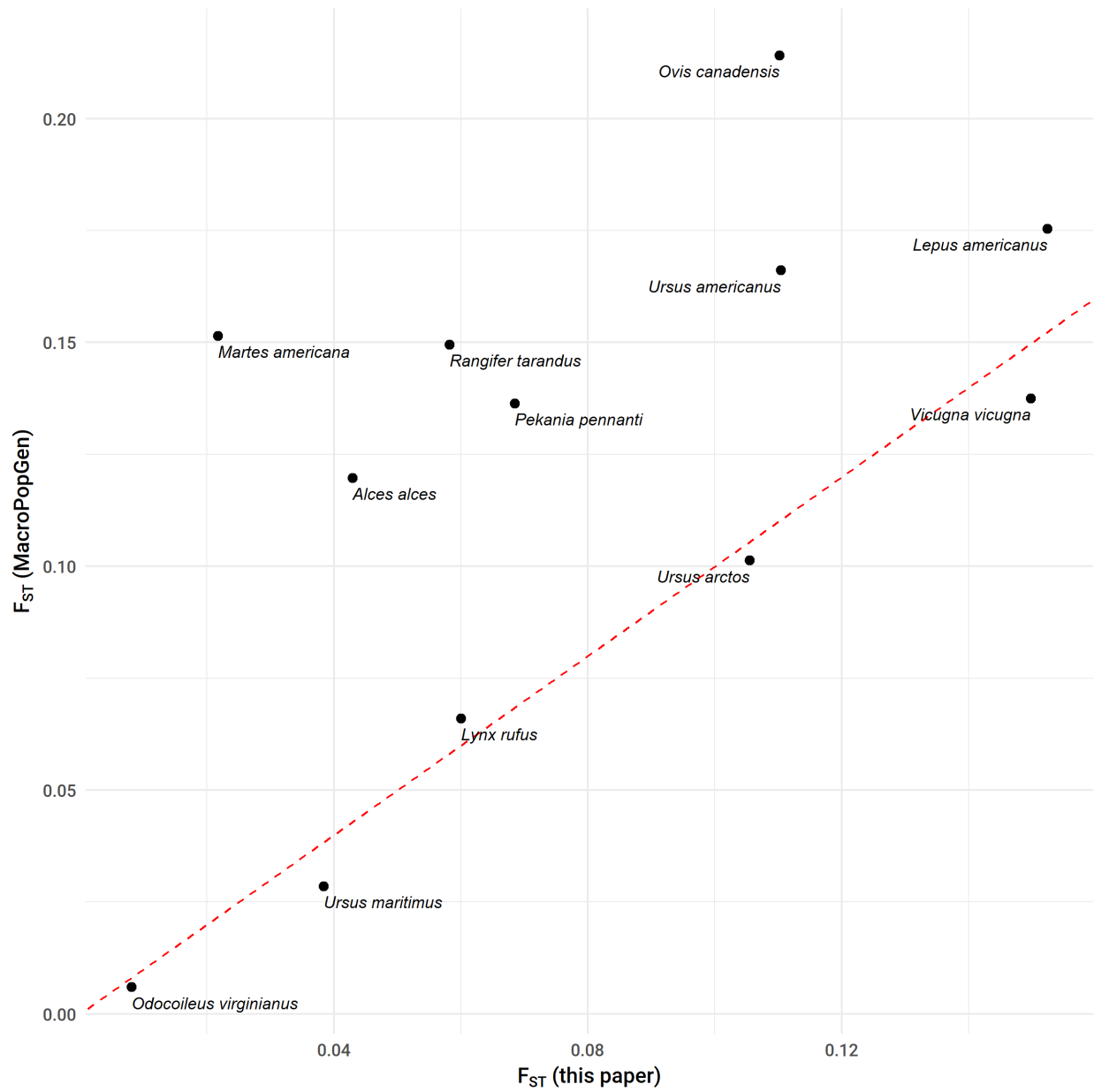


Figure S4. Observed MacroPopGen F_{ST} versus F_{ST} values predicted based on a model derived from the data analyzed here. Plots show predictions for individual datasets in the MacroPopGen database (left, points colored according to species; $CV = 1.04$) and predictions of the species mean F_{ST} averaged across datasets (right; $CV = 0.98$). The red dashed line indicates a perfect correlation.

