

Permutation tests for comparative data

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Abstract

The analysis of patterns in comparative data has come to be dominated by least-squares regression, mainly as implemented in phylogenetic generalized least-squares (PGLS). This approach has two main drawbacks: it makes relatively restrictive assumptions about distributions and can only address questions about the conditional mean of one variable as a function of other variables. Here I introduce two new non-parametric constructs for the analysis of a broader range of comparative questions: phylogenetic permutation tests, based on cyclic permutations and permutations conserving phylogenetic signal. The cyclic permutation test, an extension of the restricted permutation test that performs exchanges by rotating nodes on the phylogeny, performs well within and outside the bounds where PGLS is applicable but can only be used for balanced trees. The signal-based permutation test has identical statistical properties and works with all trees. The statistical performance of these tests compares favorably with independent contrasts and surpasses that of a previously developed permutation test that exchanges closely related pairs of observations more frequently. Three case studies illustrate the use of phylogenetic permutations for quantile regression with non-normal and heteroscedastic data, testing hypotheses about morphospace occupation, and comparative problems in which the data points are not tips in the phylogeny.

Introduction

For a biologist interested in the role of natural selection in evolution, questions about relative trait values are easier to address than questions about absolute trait values. For example, “do bears from colder climates have longer fur” is far more analytically tractable than “is long hair an adaptation for cold climates,” even if the latter is the original question of interest (Sober and Orzack 2003). Comparative or cross-species data are a fruitful source of insights into how natural selection works in populations, and also into broad-scale phenomena that are interesting in themselves, but their analysis is non-trivial. Comparative data often carry a detectable signal of the phylogenies on which they evolved, and covariation between the trait values of close

32 relatives can cause serious problems for a statistical analysis, most conspicuously in the form of
33 inflated false positive rates (Felsenstein 1985). The dominant paradigm for the past several
34 decades of comparative research was established by Felsenstein (1985), who showed that the
35 independent values in a comparative analysis are not the trait states at the tips of a phylogeny but
36 their divergences (or contrasts) at phylogenetic splits. Unlike the raw trait values, these
37 “phylogenetically independent contrasts” (PICs) can be safely analyzed with least-squares
38 regression. Phylogenetic generalized least squares (PGLS; Grafen 1989) was developed as a
39 more general comparative framework that can accommodate non-linear relationships via link
40 functions (for example, phylogenetic logistic regression; Ives and Garland 2010), trees with
41 polytomies, and a variety of evolutionary models. PGLS is a kind of generalized least squares
42 regression that uses a phylogeny as the variance-covariance matrix, and it returns identical
43 results as the PIC approach in its simplest form.

44 PICs/PGLS have enjoyed immense success as a framework for understanding
45 relationships among traits in comparative data while accounting for phylogenetic autocorrelation
46 (Symonds and Blomberg 2014), but they have two chief limitations. First, as regression tests
47 they are assumption-rich: their reliability depends on, among other things, the residuals being
48 normally distributed and homoscedastic (equal variance across the values of the predictors)
49 (Mundry 2014). The other limitation is that least-squares regression is a rather specific analytical
50 framework: questions about the relationship between one or more variables and the conditional
51 mean of another variable occupy only a small corner of the universe of biologically interesting
52 comparative problems. This has pernicious implications for the use of phylogenetic regression as
53 the “go-to” method among comparative biologists. In the last section of this paper I highlight
54 three examples of comparative problems that are off-limits to PGLS: quantile regression,
55 morphospace occupation, and ecogeographic rules. PICs/PGLS is quite powerful within rather
56 circumscribed bounds (Orzack and Sober 2001), but methods that promote the creative
57 exploration of questions and datasets outside those bounds can only improve comparative
58 biology. Here I develop phylogenetically informed permutation tests, validate them with toy
59 scenarios, and illustrate their use with empirical case studies. The first of these tests generates a
60 set of nulls using cyclic permutations and is a conceptually straightforward extension of an
61 existing test, but it can only be used with balanced trees. The second conserves the phylogenetic

62 signal in the data, has identical statistical properties to the first, and can be used with any
63 phylogeny.

64

65 **Phylogenetic permutation tests**

66 Permutation testing is widespread for some questions in evolutionary biology – for
67 example, in tests of phylogenetic signal (Blomberg et al. 2003) – but strangely has not permeated
68 to comparative testing (with one important exception, discussed below). The gist of a
69 permutation test is to take as a null distribution the set of test statistics associated with every
70 unique rearrangement (or permutation) of the data and to compare the empirical test statistic with
71 this distribution (Good 2000). In each of these permutations the “labels” on at least one variable
72 in the dataset are randomly rearranged, breaking the empirical association between variables
73 without changing their distributions. The proportion of permutations in which the test statistic is
74 at least as extreme as the empirical one is taken as the probability of obtaining the results under
75 the null hypothesis: the p-value (Perezgonzalez 2015). For example, the subject in Fisher’s
76 famous “Lady Tasting Tea” experiment correctly guessed the method of preparation for 8 cups
77 of tea, and Fisher used permutations of the order of guesses to determine that guessing randomly
78 would have achieved this result with a low probability of $p = 1/70$. This example was simple
79 enough for every possible permutation to be enumerated analytically, but for bigger datasets this
80 can be computationally infeasible, so in practice the distribution is typically estimated by
81 permuting randomly many times (Good 2000). Many “flavors” of permutation test have been
82 developed, differing mainly in the null distribution they generate (Anderson 2001). The primary
83 virtue of the permutation test is its elegance: unlike parametric tests, it does not rely on
84 theoretical probability distributions (the population of interest is the empirical one), and it can be
85 used with a broader range of test statistics (Good 2000).

86 Despite its strengths, the ordinary permutation test cannot be applied to data that evolved
87 on phylogenies. The test is, in a sense, distribution-free, but not assumption-free: permutation
88 tests assume among other things that the observations being shuffled are *exchangeable*, meaning
89 that rearrangements of those observations have the same joint probability distribution (Anderson
90 2001). This is quite close to the assumption in least-squares regression that variables are
91 independent and identically distributed, and these assumptions are violated by the complex
92 covariance structure of comparative data. In other words, because the traits of closely related

93 taxa tend to covary due to their shared evolutionary history, comparative data are not
94 exchangeable. However, a modified test that uses phylogenetic information to preserve
95 exchangeability can be used for sound non-parametric hypothesis-testing with comparative data.

96 *Lapointe-Garland phylogenetic permutations*

97 Lapointe and Garland (2001) proposed a permutation test for comparative data in which
98 pairs of values at the tips are exchanged with probability proportional to their phylogenetic
99 proximity, such that the most probable exchange is between a trait value and itself (Fig. 1A).
100 This approach uses a relatedness matrix which can be “flattened out” using a parameter k ; for
101 values of k higher than one the test approaches an ordinary permutation test. This was the first
102 and apparently the only previous attempt at developing a comparative permutation test.

103 Although the test is less vulnerable than the ordinary permutation test to phylogenetically
104 induced false positives, it has several undesirable properties. One of these is the high rate of
105 exchanges between an observation and itself (Fig. 1A), or auto-exchanges, which results in a set
106 of permutations that is tightly constrained around the empirical statistic (Appendix 1). This
107 should reduce statistical power because the permutations look so much like the empirical
108 arrangement. In this respect the Lapointe-Garland (LG) test also strays from one of the essential
109 features of permutation tests: enumerating each unique rearrangement of the data. The high rate
110 of auto-exchanges has the effect of up-weighting some possible rearrangements over others; it is
111 not clear why it would be desirable to give more weight to rearrangements that look more like
112 the empirical one. The rate of auto-exchanges can be dampened by increasing the value of k ,
113 which makes the exchange matrix flatter, but that defeats the point of incorporating phylogeny.
114 Moreover, there is no principled way to choose a value of k above one, nor is there a clear use-
115 case for permutations that are only partially informed by phylogeny. Another theoretical problem
116 with LG permutations is that they do not conserve phylogenetic signal, the key feature that
117 makes interpreting comparative datasets difficult. For the leftmost tree in Fig. 1C, the
118 phylogenetic signal of LG permutations varies by a factor of 2.3.

119 Simulations show these features of the LG approach have consequences for its statistical
120 performance. For instance, one desirable feature of a significance test is that the rate of false
121 positives should be exactly equal to the significance level: thus, 5% of cases in which the null
122 hypothesis is true should have $p < 0.05$. I tested the false positive rate of the LG permutation test
123 by simulating uncorrelated Brownian Motion evolution of two continuous traits on a rooted 8-

124 taxon tree with two polytomies of four tips each. I computed the absolute correlation coefficient
125 between the two simulated traits and tested it with an LG permutation test (500 permutations) for
126 each of 1000 pairs of simulated traits (Fig. 2). I ran the same test with independent contrasts,
127 after making the tree amenable to PICs by making the two 4-taxon polytomies in the tree into
128 pectinate subtrees with added branches having length 0. Unlike independent contrasts, LG
129 permutation tests yielded non-uniformly distributed p-values, returning intermediate values most
130 frequently (Kolmogorov-Smirnov test against a uniform distribution, $p = 0.011$). In other words,
131 the p-values from this test do not tell the user what they are supposed to: the probability of
132 observing a statistic at least as extreme as the empirical one under the null hypothesis. I also
133 evaluated the false negative rate with the same procedure, except the two simulated traits were
134 correlated with an evolutionary covariance of 0.75. LG permutation tests return false negatives at
135 higher rates than independent contrasts: $p < 0.05$ for 469 of 1000 simulations of truly correlated
136 evolution, compared with 564. The LG phylogenetic permutation test is a valuable and
137 interesting non-parametric approach to comparative data, but, motivated by the conceptual and
138 statistical problems outlined here, I develop two new phylogenetically informed permutation
139 tests. The cyclic permutation test is a conceptually straightforward extension of an existing class
140 of permutation tests that can only be used with balanced trees; the signal-based permutation test
141 has identical statistical properties to the first and can be used with any phylogeny.

142 *Cyclic permutations*

143 An elegant solution to the problem of relatedness in comparative data can be found in the
144 restricted permutation test, in which rearrangements are restricted to only occur between
145 exchangeable data points or sets of data points (Anderson 2001). As a non-phylogenetic
146 example, an investigator testing the significance of a correlation between environmental
147 variables sampled in different regions might consider permuting only within regions and not
148 across them, especially if those variables were spatially autocorrelated by region. The resulting
149 restricted permutations would retain the same kind of spatial autocorrelation as the empirical
150 data. In a comparative dataset, the exchangeable units are not the values at the tips but the
151 descendants of each node in the tree. This is similar to Felsenstein's (1985) observation that
152 contrasts at nodes rather than tip values are independent of one another, and similar also to the
153 "radiation principle" that motivates Grafen's (1989) PGLS. A set of phylogenetically informed
154 permutations can therefore be generated with cyclic permutations of the values at the tips; that is,

155 by randomly rotating the descendants of each internal node for at least one variable in the dataset
156 (Fig. 1B). A statistic calculated for the set of these permuted datasets can be compared with the
157 empirical one in what is here called a cyclic permutation test. Because the units being permuted
158 can either be tip values (for the shallowest internal nodes) or sets of tip values (for deeper nodes),
159 this is a form of hierarchical restricted permutation.

160 The cyclic permutation test performs at least as well as independent contrasts and lacks
161 the statistical issues of the LG permutation test. In the test for false positives (Fig. 2), the set of
162 p-values is indistinguishable from a uniform distribution (Kolmogorov-Smirnov test, $p = 0.370$),
163 which is ideal. In the test for false negatives with cyclic permutations, p was below 0.05 for
164 702/1000 simulations, corresponding to a false negative rate of around 30% (Fig. 2).
165 Interestingly, this is a better rate than what independent contrasts recovered (p below 0.05 for
166 564/1000 simulations). This indicates that the cyclic permutation test and PICs have at least
167 comparable statistical power, even though the former is a non-parametric test.

168 Cyclic permutations will change an unbalanced tree's two-dimensional projection, so the
169 cyclic permutation test can only be used with a topologically balanced tree. If a trait is permuted
170 cyclically on an unbalanced tree, it will no longer share the same evolutionary history as other
171 traits in the dataset, and it defeats the point of the test – namely, to ask what kinds of patterns can
172 result from the independent evolution of different traits on the same phylogeny. Because of the
173 restriction to balanced trees, the cyclic permutation test cannot be used with most empirical
174 datasets. However, because it is so conceptually straightforward and because it works (Fig. 2), it
175 is a useful yardstick against which to measure another new approach in which permutations
176 conserve the amount of phylogenetic signal in the data.

177 *Signal-based permutations*

178 The following permutation test can be used with real phylogenies: compare an empirical
179 test statistic with the set of permutations in which phylogenetic signal is equal or sufficiently
180 close to the empirical signal (Fig. 1C). The logic here is that the only rearrangements that can be
181 meaningfully compared with empirical data are those in which trait values are just as conserved
182 on, or structured by, the phylogeny. Phylogenetic signal is quantified here with Moran's I rather
183 than another metric like Pagel's λ or Blomberg's K in the non-parametric spirit of the
184 permutation test: whereas those other metrics explicitly model the evolutionary process that
185 generated a given trait, Moran's I simply quantifies the degree to which the trait values of

186 closely-related species covary (Gittleman and Kot 1990; Appendix 2). I implement signal-based
187 permutation with a simple hill-climbing algorithm in which first the values of a trait are shuffled,
188 then randomly-selected pairs of observations are swapped if doing so brings the phylogenetic
189 signal closer to the empirical signal, and the procedure stops when the permuted phylogenetic
190 signal is within some specified tolerance of the empirical value. The test could be implemented
191 without this hill-climbing procedure, but it would make the test extraordinarily time-consuming
192 for some datasets. Because phylogenetic signal depends on the values at the tips, the
193 rearrangements that are included in the set of signal-based permutations depend on the values of
194 the trait being permuted, unlike cyclic permutations and the LG permutation test. For applicable
195 trees, the set of signal-based permutations is always at least as inclusive as the set of cyclic
196 permutations: every cyclic permutation has identical phylogenetic signal, but non-cyclic
197 permutations of a dataset can too (Fig 1B, rightmost permutation), and additional rearrangements
198 can be accepted if the specified tolerance is large enough. For example, there are $2^{(\text{number of internal nodes})} = 128$ possible cyclic permutations of the 8-taxon tree in Figure 1B but 256
199 permutations with identical phylogenetic signal. The positions of clades (C,D) and (G,H) are
200 switched in the 128 non-cyclic permutations.
201

202 Despite these striking differences from the cyclic permutation test, simulations show that
203 signal-based and cyclic permutations have apparently identical statistical properties. Like the
204 other test, the signal-based test correctly returns a uniform distribution of p values for 1000
205 simulations of uncorrelated evolution (Fig. 2, “Signal-based permutation”; Kolmogorov-Smirnov
206 test against a uniform distribution, $p = 0.413$). The false negative rate is also comparable with
207 that for the cyclic permutation test (Fig. 2; 716/1000 p-values below 0.05), and higher than that
208 for PICs. Thus, the cyclic and signal-based permutation tests do not have the problems with
209 statistical power and size that characterize the Lapointe-Garland test.

210 As a visual illustration of the two new phylogenetic permutation tests, consider their
211 application to Felsenstein’s (1985) “worst case scenario” in which uncorrelated Brownian
212 Motion evolution of two traits on a rooted tree of two polytomies with 20 tips each (all branch
213 lengths equal) generates a spurious correlation among traits (Fig. 3A). An ordinary permutation
214 test yields a distribution of mainly low absolute correlation coefficients (Fig. 3B) and a very high
215 level of significance ($p < 0.001$). The investigator who makes the mistake of treating all tip
216 values as exchangeable incorrectly rejects the null hypothesis of independent evolution.

217 Conversely, the distribution of correlation coefficients for 1000 cyclic permutations is centered
218 close to the empirical correlation coefficient (Fig. 3B), yielding a p-value of 0.31. Because of the
219 clustering of trait values within subclades, every cyclic permutation preserves a relatively strong
220 correlation coefficient: 95% of the cyclic permutations have $|r|$ between 0.34 and 0.65. The null
221 distribution generated by signal-based permutations depends on the tolerance: a set of 1000
222 signal-based permutations with the broadest possible tolerance (2) is statistically
223 indistinguishable from an ordinary permutation test (Kolmogorov-Smirnov test, $p = 0.7226$)
224 because the phylogenetic signal of every possible permutation is within its tolerance (Fig. 3B).
225 For smaller tolerances, the distribution of test statistics for signal-based permutations more
226 closely approximates the set of cyclic permutations (Fig. 3B), such that with a margin of 0.01
227 (Moran's I of permuted variable Y between 0.512 and 0.532) they are statistically
228 indistinguishable ($p=0.536$). Thus, signal-based permutations converge on the statistical
229 properties of cyclic permutations.

230 Interestingly, phylogenetic permutation tests succeed in a case where PICs and PGLS
231 both fail: a second “worst case” constructed by Uyeda et al. (2018). In this scenario, simulated
232 traits evolve in the same way and on the same phylogeny as in Felsenstein's worst case, but with
233 one modification: a single extreme shift in both traits near the root generates a contrast that is a
234 strong enough outlier to make the two traits appear significantly associated, even when
235 “correcting for phylogeny.” PICs/PGLS incorrectly recover significant relationships between
236 traits because these methods are parametric, and their assumptions are violated by the dramatic
237 outlier. The cyclic permutation test is unburdened by these assumptions: the extreme outlier is
238 incorporated into every permutation, and the test correctly yields a non-significant result
239 (Appendix 3). Likewise, the only rearrangements of the data that conserve phylogenetic signal
240 are those in which exchanges only occur within clades and not between them, so a signal-based
241 permutation test succeeds in the same way. Cyclic and signal-based permutations both represent
242 reasonable null models against which to compare empirical patterns, but only the latter is
243 applicable to real trees, so I use signal-based permutation tests to explore the following case
244 studies.

245

246

Case studies

247 The preceding sections established that phylogenetic permutations perform at least as
248 favorably as PICs in “toy scenarios” in which the truth is known. These scenarios involved
249 modeled BM evolution of traits with normal distributions, and the only test statistic considered
250 was the correlation between two traits. PICs/PGLS perform comfortably within these bounds. In
251 the following case studies, I use phylogenetic permutation to explore scientific questions that are
252 effectively off-limits to PGLS-type methods because they involve strange distributions and test
253 statistics beyond the least-squares regression framework. The first case study involves quantile
254 regression on a heteroskedastic dataset with a non-normal response variable. The second
255 explores the statistical significance of patterns of morphospace occupation. The third tests an
256 ecogeographic rule: the data points are not tips in the phylogeny but the aggregate property of all
257 the tips that occur in each geographic area.

258 The statistical significance of some of these findings could potentially be tested by
259 comparing empirical statistics with null simulations rather than permutations, like what Mahler
260 et al. (2013) used to demonstrate exceptional convergence in anoles. However, this requires
261 assumptions about distributions and the evolutionary processes that generated a dataset which an
262 investigator may not want or be able to make. If a dataset exhibits a more extreme test statistic
263 than a set of simulations, is it because there was a mechanistic association between those traits,
264 or because the simulations were unrealistic? Such questions may be hard to answer and are
265 avoided by taking the non-parametric approach.

266 *Quantile regression and peculiar distributions: arm number in feather stars*

267 Saulsbury and Baumiller (2020) investigated a wedge-shaped relationship between
268 absolute latitude and arm number among feather stars, a group of suspension-feeding marine
269 echinoderms: species near the poles typically have around 10 arms, whereas those around the
270 equator have between 5 and 150. Arm number varies widely within many families, but across the
271 dataset it has a strange distribution, probably due to the unique and complex ontogeny of feather
272 star arms (Shibata and Oji 2003): about half the species in the dataset have exactly 10 arms, and
273 the rest of the distribution is markedly right skewed. More importantly, this non-normality also
274 characterizes the residuals in a PGLS regression of arm number, and $\log(\text{arm number})$, on
275 absolute latitude. Another aspect of the dataset that poses obvious problems for least-squares
276 regression is also the dataset’s most biologically interesting feature: arm number is
277 heteroskedastic across absolute latitude. Beyond these more technical challenges, questions

278 about the spread of a response variable as a function of a predictor cannot be readily addressed
279 with least-squares regression. Instead they are the purview of quantile regression, which
280 estimates quantiles (for example, the median, or the 10th percentile) conditional on predictors.
281 There is not currently an equivalent to quantile regression in the PGLS framework. As such, the
282 authors used signal-based phylogenetic permutation tests to consider whether the latitudinal
283 gradient in arm number could have plausibly emerged through independent evolution on feather
284 star phylogeny.

285 Although both absolute latitude and arm number exhibit phylogenetic signal, and thus
286 might be prone to spurious associations, the empirical relationships between the two are more
287 extreme than almost all phylogenetic permutations. The 90th and 95th conditional percentiles,
288 which characterize how maximum arm number relates to latitude, were significantly negative (p
289 = 0.017 and 0.009, respectively), as was Spearman's rank-correlation coefficient ($p < 0.001$).
290 Concluding that the pattern could not be explained away as the result of random evolution, the
291 authors drew on ecological and functional morphological evidence to argue that a latitudinal
292 gradient in the intensity of predation represented the most plausible explanation for their
293 findings. This simple case study illustrates the value of a comparative method that makes
294 minimal assumptions about the distribution of the data. It also hints at the extent of the patterns
295 that can be evaluated with phylogenetic permutation, although that is more fully illustrated by
296 the following examples.

297 *Morphospace occupation: Triassic ammonoids*

298 Why are some theoretically possible morphologies not realized in nature, and why are
299 some realized more frequently than others? These questions are the domain of theoretical
300 morphology, a subdiscipline catapulted to the forefront of evolutionary biology for a time by
301 David Raup. He found (1966) that the breadth of shell morphologies realized by mollusks and
302 brachiopods was surprisingly well-summarized by a model in which a generating curve or whorl
303 increases in size as it revolves around an axis. Shell geometry is controlled by three parameters:
304 whorl expansion rate, translation of successive whorls along the axis, and the distance of
305 successive whorls from the shell axis. Interestingly, most theoretically possible combinations of
306 parameter values are not realized in nature; Raup cautiously submitted that either these
307 unrealized forms were physiologically impossible, or shell-building invertebrates simply had not
308 had time to reach those parts of morphospace yet. A companion paper (Raup 1967) focused on

309 ammonoids, an extinct group of mostly “planispiral” mollusks in which typically no whorl
310 translation occurs and variation is constrained along two axes of theoretical shell morphospace:
311 the distance of successive whorls from the axis (D), and the whorl expansion rate (W) (Fig. 4A).
312 Again, much of the rectangle defined by ammonoid occupation in D - W space is unoccupied – for
313 example, almost no ammonoids fall above the line $W = 1/D$ (Fig. 4A). Shells above this curve
314 are open-coiled, making them, among other things, weaker and easier for a predator to crush. For
315 shells under this curve, each whorl can incorporate part of the previous whorl in its construction,
316 so open-coiled shells ($W > 1/D$) also waste the building materials they otherwise would have
317 saved. Thus, the patterns in theoretical morphospace occupation are interesting because of the
318 underlying fitness surface they suggest.

319 The problem with inferences of selective forces from the pattern of morphospace
320 occupation is that they rely on the equilibrium assumption (Lauder 1982): namely, that the
321 phenotypes under study are at equilibrium with the selective forces that act on them. The
322 alternate explanation for un- or under-occupied regions of morphospace is that, by chance,
323 ammonoids simply have not had time to reach those regions yet – in other words, the system is
324 historical and not at equilibrium. Raup (1967) raised this possibility, but admitted that in order to
325 make headway he had to “assume that the observed morphology has had, in evolution, a
326 selective advantage over other possible morphologies.” Subsequent studies have made the same
327 assumption: for example, Tendler et al. (2015) tested whether ammonoids fill out a triangle in D -
328 W space as a demonstration of Pareto optimality theory, which predicts that functional
329 “archetypes” should form the vertices of polygons in trait space (Fig. 4A). They tested whether
330 the ammonoid data are more triangular than the set of ordinary permutations, but this procedure
331 incorrectly assumes that the data are exchangeable, or in other words that each data point
332 obtained its morphology independently – a problem pointed out by Edelaar (2013) for another
333 study of Pareto optimality. The equilibrium assumption leaves comparative studies vulnerable to
334 the kinds of false positives discussed by Felsenstein (1985) in which a pattern apparently
335 supported by a high number of replicates actually only represents a few evolutionary events.
336 Theoretical morphology has not been incorporated with phylogeny in the way other comparative
337 subdisciplines have in recent decades. However, it is not amenable to PGLS because it is not a
338 regression problem: the question is not about the conditional mean of a response variable but
339 about why certain combinations of traits are unrealized.

340 The phylogenetic permutation approach is a promising way forward for theoretical
341 morphology because it can be used to ask what kinds of patterns in morphospace occupation can
342 emerge without any dependence between traits. If empirical patterns fall outside the range of
343 phylogenetic permutations, more interesting evolutionary explanations for the pattern in
344 morphospace occupation can be explored – for example, certain morphologies could be
345 unrealized because they are less fit. No broad-scale phylogeny of ammonoids is available, so I
346 used taxonomy as a polytomy-rich phylogeny to explore morphospace occupation in the database
347 of 322 Triassic ammonoid genera from McGowan (2004). These genera belong to 79 families in
348 18 superfamilies. This is a very coarse way to approximate phylogeny, so this exploration should
349 be taken as a proof of concept and a hint at the role of contingency in ammonoid evolution.

350 I used ordinary and signal-based phylogenetic permutations to test the significance of two
351 test statistics: the number of genera over the $W=1/D$ line (6/322 genera), and the triangularity of
352 the dataset in D-W space, defined as the ratio of the area of the convex hull to the area of the
353 smallest triangle that encloses all the data (triangularity = 0.8535; Fig. 4A; Appendix 4). Both D
354 and W have low signal on the “phylogeny”, with values of Moran’s I of 0.072 and 0.049,
355 respectively. So, inasmuch as ammonoid taxonomy approximates phylogeny, the various
356 ammonoid clades appear to have independently explored a lot of D-W space: for example, there
357 are five superfamilies that each occupy more than half the area of the total convex hull. In a
358 system characterized by this much exploration of morphospace, it seems unlikely that
359 particularly strong patterns could emerge from random chance alone. The phylogenetic
360 permutation test quantifies this preliminary impression: $p < 0.001$ for both test statistics for both
361 ordinary and phylogenetic permutations (Fig. 4B-C). In other words, all phylogenetic
362 permutations of the data have more open-coiled genera and are less triangular than the empirical
363 dataset. Considering phylogeny (that is, going from ordinary to phylogenetic permutations) does
364 not visibly affect the null distribution for the first test statistic; it does slightly for triangularity,
365 shifting it to the right. So, because of phylogeny there is a slight tendency for permuted datasets
366 to look more triangular, but not enough to make a difference for the p-value.

367 Thus, the independent evolution of shell growth parameters D and W constitutes a poor
368 explanation for both the triangularity of the dataset and the paucity of open-coiled genera. One
369 could easily imagine a hypothetical phylogenetic history for which a non-significant result would
370 be obtained – for example, if every ammonoid with $D > 0.3$ were part of the same clade, it would

371 be easier to explain away the pattern of morphospace occupation as a historical accident. The
372 phylogenetic permutation test is well-suited for this problem because characterizing the
373 biologically interesting features of morphospace occupation often requires the use of creative or
374 novel statistics. Note that this is not the only way to evaluate the evolutionary “significance” of
375 morphospace occupation: Tendler et al. (2015) showed that ammonoids refilled roughly the same
376 region of morphospace several times after mass extinctions, representing semi-independent
377 replicates. In the final case study, I explore a comparative problem in which the data points are
378 not tips in the phylogeny.

379 *Ecogeographic rules: Thorson’s rule in muricid gastropods*

380 Some of the most productive hypotheses in biology predict the way some biological
381 feature changes across space. Well-known examples of “ecogeographic rules” like these include
382 Bergmann’s rule, the tendency for endotherms to be larger toward the poles (Olalla-Tárraga
383 2011), and Rapoport’s rule, the putative tendency for species’ latitudinal ranges to be smaller in
384 the tropics (Stevens 1989). The analysis of ecogeographic rules entails an interesting and under-
385 researched problem: species typically exist in more than one place, rather than at a single point
386 as in other kinds of comparative studies. It might seem that a straightforward comparative
387 analysis could address this by using a summary statistic of the range of each species, such as the
388 range midpoint, and indeed many studies take this shortcut. However, such an approach removes
389 biological information and is susceptible to false positives, especially if the trait in question
390 corresponds with range size in some way (Saulsbury and Baumiller 2020; Colwell and Hurtt
391 1994). In the most well-known and straightforward example, a test for a relationship between
392 absolute latitudinal midpoint and range size tends to recover strong negative relationships even
393 none really exists: geometrically, large ranges cannot be centered at high latitude, so these taxa
394 have their latitudinal midpoints “pulled” toward the equator (Colwell and Hurtt 1994). An
395 alternative approach is to consider the ecogeographical data as such – that is, as a set of places
396 and the aggregate properties of all the species in each place (Stevens 1989) – but this is
397 analytically fraught as well. Such data are beset not only by the phylogenetic autocorrelation that
398 complicates other comparative studies, but also by spatial autocorrelation to the degree that
399 species occur in multiple places (Rohde et al. 1993). Here I show that both the phylogenetic
400 permutation test can circumvent both sources of autocorrelation using a case study of larval
401 development across latitude in muricid gastropods.

402 Thorson's rule predicts that the larvae of marine invertebrates near the equator are more
403 likely to be planktotrophs – feeding larvae that persist in the water column for a long time –
404 whereas toward the poles there should be a predominance of non-feeding larvae, including direct
405 developers and lecithotrophs (yolk-supplied larvae) (Thorson 1950). Thorson proposed that
406 vulnerable planktotrophic larvae would not be able to cope with the extreme conditions and
407 variable food supply at high latitudes, but this mechanism and the latitudinal pattern have
408 subsequently received mixed empirical support (Marshall et al. 2012). Yet the idea persists:
409 Pappalardo et al. (2014) claimed support for Thorson's rule in a dataset of 44 muricid gastropod
410 species (Fig 5A). A logistic PGLS regression of larval development (planktotrophic vs. non-
411 feeding) on sea surface temperature [taken either from a single confirmed occurrence (69%) or
412 from the latitudinal midpoint of each species (31%)] recovered marginally significant
413 relationships: $p = 0.087$ for the regression of feeding (planktotrophic) vs. non-feeding mode on
414 temperature, and $p = 0.045$ for the regression of pelagic (planktotrophic and lecithotrophic) vs.
415 non-pelagic mode on temperature. Analyzing the same dataset, I found a similar degree of
416 support in a PGLS logistic regression of larval development on latitudinal midpoints (Appendix
417 5). Other recent studies of Thorson's rule use latitudinal or environmental midpoints as well
418 (Ibáñez et al. 2018; Ewers-Saucedo and Pappalardo 2019), presumably because the PGLS
419 framework requires it. Notably this seems to be a recent development, as Thorson and others
420 who worked on this problem since were mostly considering the proportion of planktotrophic
421 species at each latitude (Thorson 1950; Mileikovsky 1971; Jablonski and Lutz 1983; Collin
422 2003). Importantly, the use of midpoints can be vulnerable to complications involving range
423 size: for example, if planktotrophic species have larger ranges, it would artificially strengthen the
424 relationship between latitude and development by dragging the latitudinal midpoints of wide-
425 ranging species toward the equator (Colwell and Hurtt 1994). In fact, the broad geographic
426 ranges of feeding larvae are famous among invertebrate zoologists (Jablonski 1986), and the
427 median latitudinal range of planktotrophic species in the muricid dataset is 3.25 times that of
428 non-planktotrophs (Fig 5A). Using a latitude or temperature value selected randomly from the
429 range might not be biased like the midpoint method is, but is not an ideal solution because it
430 removes information and adds noise.

431 If instead the ecogeographic data are considered as such – for example, with a plot of the
432 percentage of species with planktotrophic larvae in each 1° latitudinal bin – the trend is still

433 apparent, with a strong correlation of $r = 0.927$ (Fig. 5B). A non-phylogenetic significance test
434 that nevertheless accounts for spatial autocorrelation can be performed by permuting modes of
435 larval development randomly across the tips of the phylogeny and re-computing the correlation
436 coefficient (Fig. 5C). The resulting absolute correlation coefficients are spread evenly between 0
437 and 1, yielding marginal statistical significance with a p-value of 0.033. We can take both spatial
438 and phylogenetic autocorrelation into account with signal-based phylogenetic permutations of
439 mode of larval development. Phylogenetic signal of planktotrophic vs. non-planktotrophic
440 development is high (Moran's $I = 0.60$), and indeed larval development only appears to have
441 transitioned on the phylogeny a few times, providing an investigator with very low sample size:
442 the most parsimonious history of development involves only three transitions to or away from
443 planktotrophy. Accordingly, almost all phylogenetic permutations have high absolute correlation
444 coefficients, from which the empirical correlation is statistically indistinguishable ($p = 0.387$).
445 Thus, the muricid dataset cannot provide strong evidence against the completely independent
446 evolution of latitude and larval development. Notably, the authors focused on temperature not
447 latitude; it is unclear if a similarly non-significant result would be obtained for the correlation
448 between temperature and larval development, but temperature and latitude are closely correlated,
449 and the same analytical problem applies because species occupy a range of temperatures.

450 Ecogeographic data present an interesting challenge to the comparative biologist because
451 the data points, cast most directly, do not represent tips in the phylogeny but the aggregate
452 properties of all the tips in the phylogeny that occur in each place. It might be possible to
453 consider such data in a PGLS framework, but it would require the specification of a rather
454 complex variance-covariance matrix. Crucially, this phylogenetic permutation test does not
455 provide evidence *against* Thorson's rule in this group. At the pattern level, the group is a clear
456 example of the rule, with a strong negative correlation between latitude and the proportion of
457 species with planktotrophic larvae. This trend probably has important implications for their
458 modern ecology and future evolution, because it predicts, for example, that low-latitude
459 planktotrophic species should be buffered against extinction by their broad ranges (Jablonski and
460 Lutz 1983; Jablonski 1986). However, the key point is that, with phylogenetic and spatial
461 autocorrelation this strong, such a trend could have easily arisen without any mechanistic
462 relationship between latitude and larval development. In fact, given the distribution of
463 phylogenetic permutations (Fig. 5C), it would be much more surprising to find no latitudinal

464 trend in larval development. This might explain why so many groups appear to follow the rule
465 (Ibáñez et al. 2018), especially since mode of larval development appears to evolve infrequently
466 among marine invertebrates (Collin 2004). It would require an exceptionally strong trend to
467 support a mechanistic Thorson’s rule in a dataset like this one – or more plausibly, a different
468 kind of data. This might mean a clade in which larval development transitions more frequently,
469 or it might mean a different kind and scale of evolutionary repetition.

470

471

Conclusions

472 The regression-based approach to comparative biology has been hugely successful, but it
473 is also inflexible: it fails for strangely distributed response variables, but more importantly, the
474 range of questions it can address is limited. Permutation tests represent a powerful alternative
475 that performs well both within and outside the bounds where PGLS is applicable. Case studies
476 illustrate the use of phylogenetic permutations for pushing comparative methods to new places.

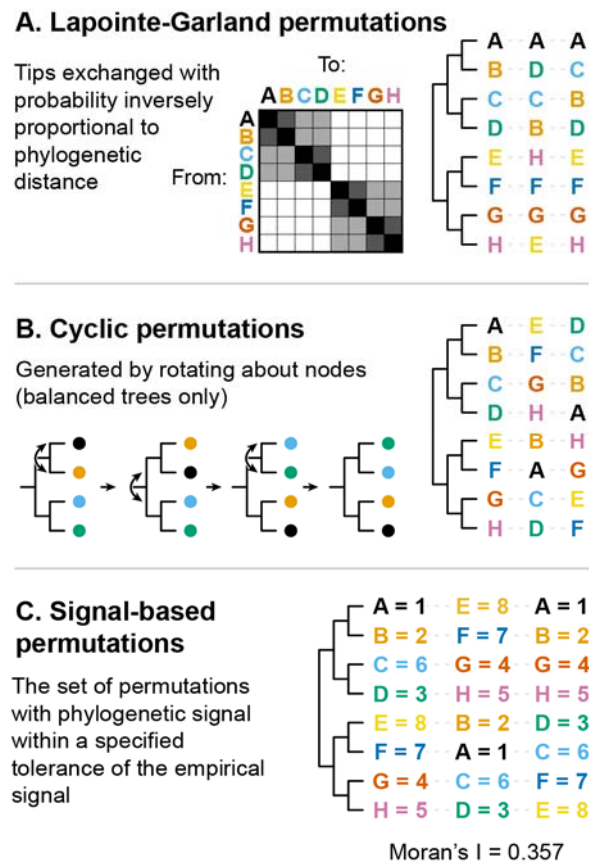
477 Rather than being a purely technical matter, the distinction between PGLS and
478 permutation-based approaches is underlain by a more substantive difference in attitude toward
479 comparative data. PGLS is typically described as a way to “correct for phylogeny” (Symonds
480 and Blomberg 2014). Other comparative methods take an even more direct approach by
481 transforming the data to “remove phylogenetic effects” (Stearns 1984; Cheverud et al. 1985;
482 Felsenstein 1985; Gittleman and Kot 1990). The implication is that comparative data have been
483 contaminated or affected by an agent called phylogeny, and that this contamination needs to be
484 isolated and removed before the real relationships in the data can be studied. It is a drawback of
485 these methods that they put the user at a remove from the raw data. Patterns in phylogenetically
486 autocorrelated data are also no less real than those in transformed data: biological phenomena
487 that could have arisen purely by chance, like Thorson’s rule in some taxa, can nevertheless have
488 real and important consequences. Transformations and corrections also remove information and
489 limit the kinds of statistics and questions that can be applied to a dataset.

490 The phylogenetic permutation test is mostly unique among comparative methods in that it
491 treats the raw data as such. The test is subject to some of the same criticisms to which all
492 frequentist tests are subject, including that statistical significance tells an investigator nothing
493 about effect size (a reaction to the widespread conflation of “significance” with importance;
494 Dushoff et al. 2019). This is true, but for many biological phenomena including the case studies

495 discussed here, the most relevant effect size is arguably the empirical test statistic. Only six of
 496 322 Triassic ammonoid genera have open-coiled shells; it is hard to imagine a more meaningful
 497 phylogenetic transformation of this test statistic. The phylogenetic permutation framework,
 498 which considers whether raw data look typical for cases of independent evolution, is in a way the
 499 reverse of the reigning paradigm of transforming comparative data or their expected covariances
 500 to fit into a regression analysis. Hopefully, these new approaches can help facilitate scientific
 501 creativity among comparative biologists.

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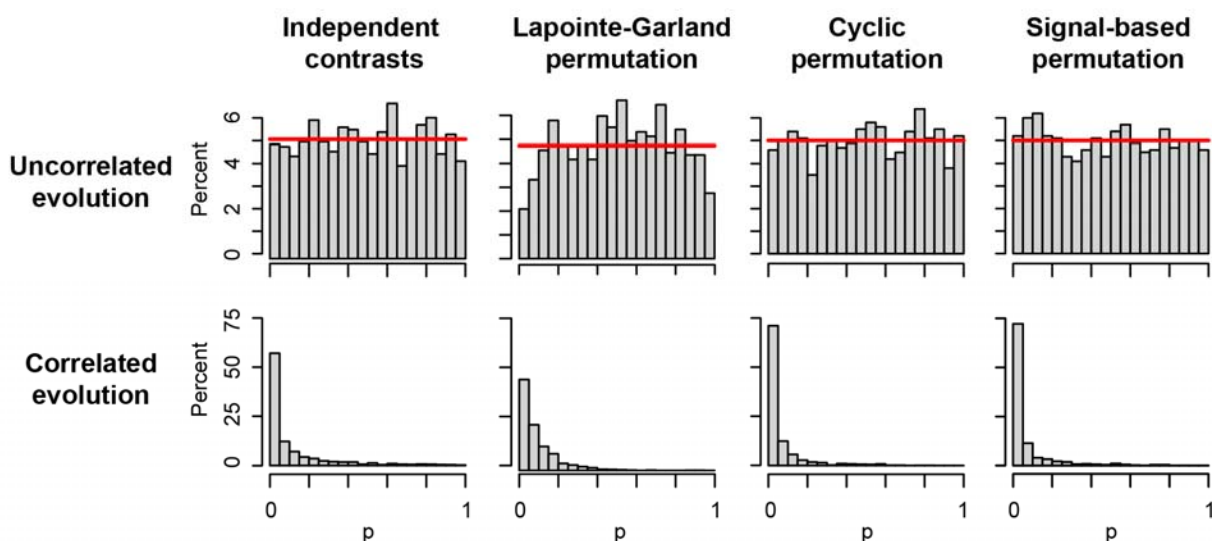
Figures



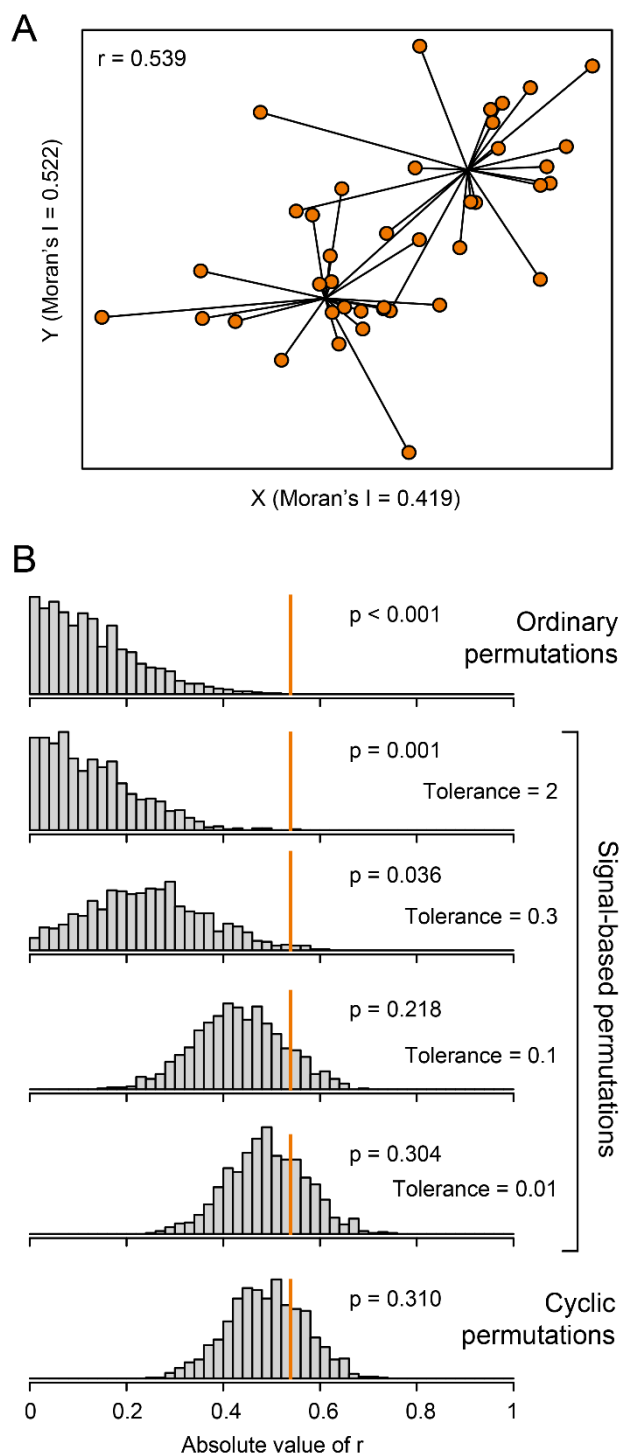
503

504 **Figure 1.** The three kinds of phylogenetic permutations discussed in this paper, with examples of
 505 each kind on a balanced, rooted tree of 8 taxa A-H. In a test, each kind of permutation is applied
 506 to at least one variable in the dataset, and a population of many such permuted datasets is
 507 compared with the empirical arrangement. **1A.** The phylogenetic permutation approach
 508 developed by Lapointe and Garland (2001). Note that many trait values do not change position
 509 across permutations because the highest probability of exchange is between a trait and itself. **1B.**
 510 Cyclic permutations: the set of permutations that can be generated by rotating about nodes in the

511 tree (double-sided arrows). **1C.** Signal-based permutations. These are more inclusive than cyclic
512 permutations: they include all possible cyclic permutations because the latter always conserves
513 phylogenetic signal, but also non-cyclic permutations that retain the same or nearly the same
514 signal (rightmost rearrangement). This is the only test in which the set of permutations depends
515 on the values at the tips.

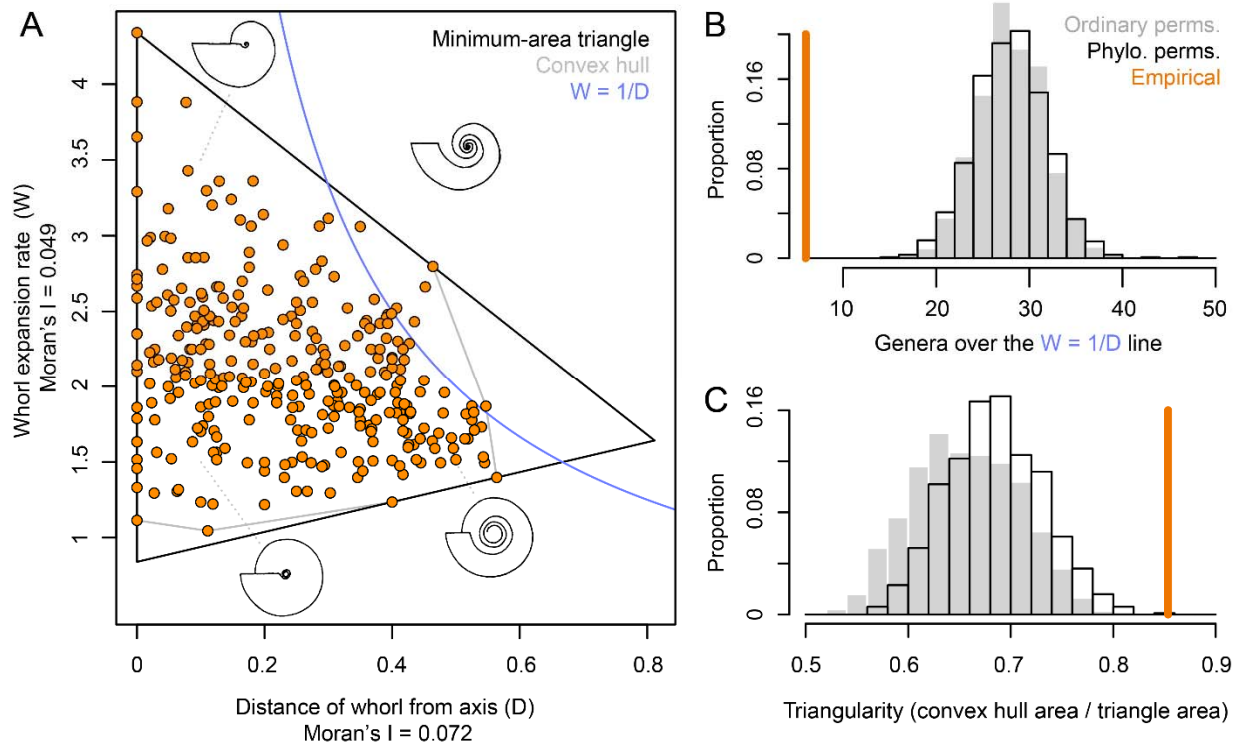


516
517 **Figure 2.** p-values for three phylogenetic permutation tests of correlation and one test with
518 independent contrasts, applied to uncorrelated evolution of X and Y (above) and correlated
519 evolution with an evolutionary covariation of 0.75 (below). Traits simulated on a rooted 8-taxon
520 tree containing two polytomies with 4 taxa each, all branch lengths equal. p-values should ideally
521 be uniformly distributed for uncorrelated evolution and as low as possible for correlated
522 evolution. Red horizontal line indicates a uniform distribution; only Lapointe-Garland
523 permutations differ significantly from this distribution. All bins have width 0.05.

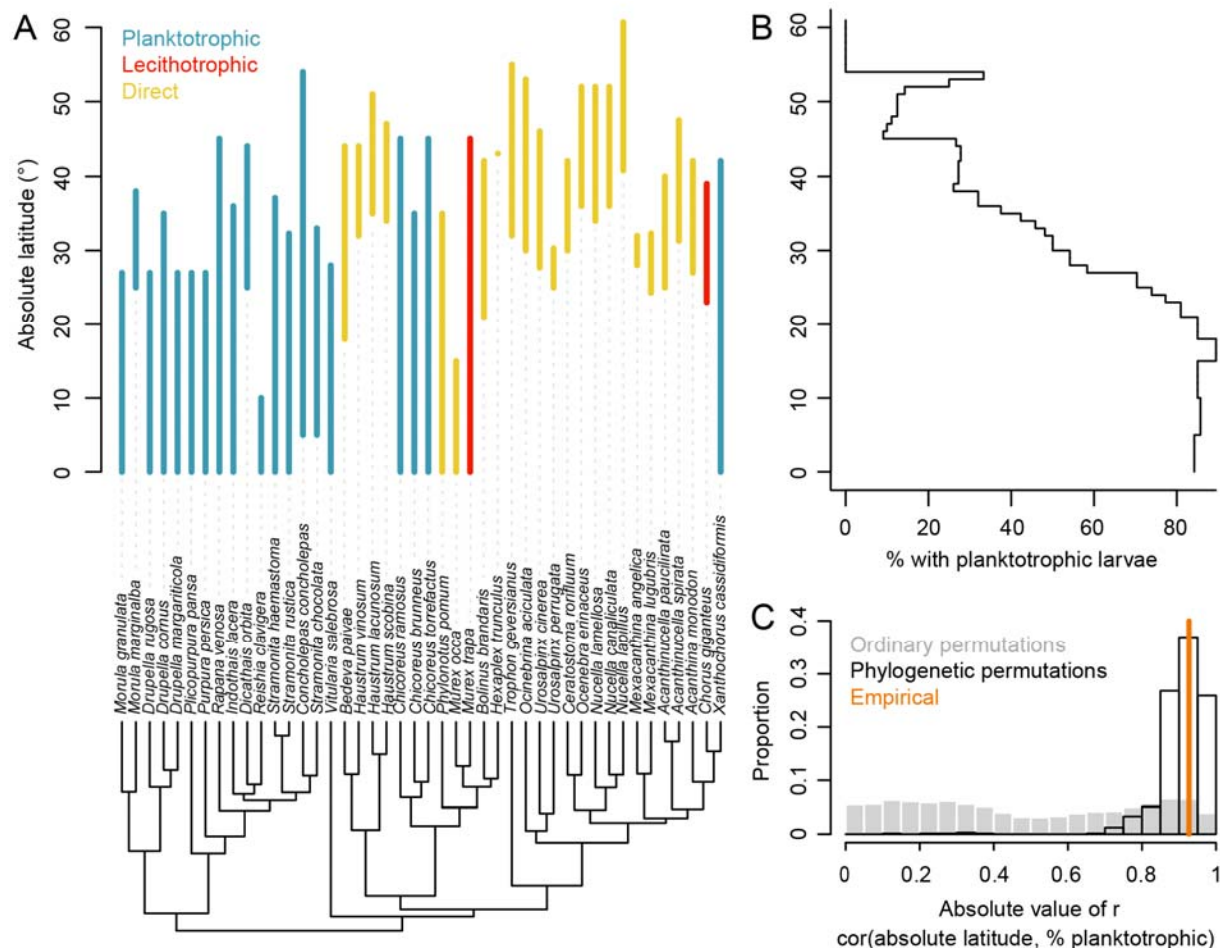


524
525 **Figure 3.** Phylogenetic permutations applied to Felsenstein's "worst case" in which two traits
526 evolve independently on a tree whose shape tends to induce spurious correlations. **3A.**
527 Scatterplot of traits X and Y with lines connecting values at the tips to ancestral state
528 reconstructions. **3B.** Histograms showing the correlation between X and Y for sets of 1000

529 permutations of the variable Y with different approaches: ordinary permutations, signal-based
530 permutations with progressively smaller signal tolerances, and cyclic permutations. With a
531 tolerance of 0.01, signal-based permutations are statistically indistinguishable from cyclic
532 permutations. Vertical orange bars indicate the empirical correlation coefficient.



533
534 **Figure 4.** Phylogenetic permutation tests applied to theoretical morphospace occupation in
535 Triassic ammonoids. **4A.** Two parameters controlling shell geometry in 322 Triassic ammonoid
536 genera from McGowan (2004). Four theoretical ammonoid shells redrawn from Raup (1967)
537 illustrate how different shell geometries correspond to different combinations of these
538 parameters. Also plotted are the convex hull around the points, the smallest possible triangle
539 around the points, and the line $W = 1/D$, above which shells are open-coiled. **4B.** The empirical
540 number of genera with $W > 1/D$ compared with the same statistic for 1000 ordinary and 1000
541 signal-based phylogenetic permutations. This statistic was taken by Raup (1967) as evidence for
542 the reduced fitness of open-coiled forms. **4C.** The empirical ratio of the area of the convex hull
543 around the data to the area of the smallest triangle that fits around the data, compared with the
544 same statistic for 1000 ordinary and 1000 phylogenetic permutations. This metric of triangularity
545 was interpreted by Tendler et al. (2015) in light of Pareto optimality theory.



546
 547 **Figure 5.** Phylogenetic permutation applied to Thorson's rule in muricid gastropods. **5A.** Mode
 548 of larval development (color-coded), absolute latitudinal range, and phylogeny for the 44 species
 549 from Pappalardo et al. (2014). **5B.** Thorson's rule plotted "as such": the percentage of species
 550 with planktotrophic larval development in each 1° bin of absolute latitude. **5C.** The correlation
 551 between absolute latitude and the percentage of planktotrophic species in each 1° latitudinal bin,
 552 shown for the empirical data, 1000 ordinary permutations of mode of larval development, and
 553 1000 phylogenetic permutations.

554

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Data availability statement

648 Code, supplementary data, and appendices are available at the following GitHub repository:

649 <https://github.com/jgsaulsbury/phyloperm>