

1 A tale of two lakes: divergent evolutionary trajectories of two *Daphnia* populations experiencing  
2 distinct environments

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16

17 **Abstract:**

18 Most studies of local adaptation substitute the correlation between spatial distance and  
19 environmental heterogeneity for the temporal dynamics over which local adaptation evolves.  
20 The availability of detailed ecological and genomic information from lake sediments provides an  
21 opportunity to study local adaptation with unparalleled clarity from the temporal perspective.  
22 Inference can be further enhanced by including multiple lakes along ecological axes to further  
23 isolate the effects of ecological change in driving local adaptation. Lakes throughout the world  
24 face the impact of numerous anthropogenically induced environmental changes. Top among  
25 these is the eutrophication of freshwaters from agriculture, development and land-use change.  
26 Here we use the genetic information recorded in lake sediments of two lakes experiencing  
27 contrasting histories of land-use change to study the evolution of local adaptation in the lakes'  
28 *Daphnia pulicaria* populations. Utilizing nextRAD derived Single Nucleotide Polymorphisms  
29 (SNPs), we studied the evolutionary trajectories of *Daphnia pulicaria* in both lakes. Using gene-  
30 environment correlations and  $F_{st}$  tests for selection we found SNPs that appear to be under  
31 selection in both lakes. Specifically, we found more outlier SNPs in the highly impacted lake  
32 using  $F_{st}$ -based tests for selection. Conversely, gene-environment tests revealed the reverse  
33 pattern. We discuss numerous facets of experimental design that must be considered when  
34 using resurrection ecology to study local adaptation and critically evaluate how they may have  
35 impacted the results of this investigation.

36 **Keywords:**

37 *Daphnia*, Genomics, RAD-Seq, Natural Selection, Resurrection Ecology, Limnology,  
38 Eutrophication

39 **Lay Summary:**

40 Resurrection ecology, the resuscitation or hatching of decades or centuries old dormant eggs,  
41 seeds or cysts provides the opportunity to study evolution in action. Here, we use resurrection  
42 ecology paired with Single Nucleotide Polymorphism (SNP) genotyping to study the evolutionary  
43 responses of two populations of *Daphnia pulicaria* to contrasting changes in the nutrient  
44 dynamics of their respective lakes. In the lake with more drastic changes in nutrient pollution,  
45 we find a stronger shift in allele frequencies through time and at a larger number of affected  
46 genomic positions compared with the environmentally more stable lake. However, Bayesian  
47 gene-environment correlations were stronger in the more stable lake reflecting higher power to  
48 detect correlations among allele frequency change and paleo-environmental variables in this  
49 location. Our results suggest that numerous factors might impact the ability to use different  
50 methodologies to detect local adaptation over time using resurrection ecology.

51 **Introduction:**

52 In his 1859 novel, *A Tale of Two Cities*, Charles Dickens compares the cities of London and  
53 Paris in the late 18th century. Juxtaposition is the central literary device Dickens uses in his  
54 novel. While bi-directional comparison is useful in literature, it can also be illustrative in  
55 biology. Specifically, in evolutionary biology, the availability of two or more populations  
56 experiencing contrasting selection regimes provides the basis for demonstrating local adaptation  
57 (Kawecki and Ebert, 2004). The occurrence of local adaptation and spatial structuring of habitats  
58 provides the basis for the diversification of lineages and the origin of biodiversity by the  
59 exploitation of ecological opportunity (Rainey and Travisano, 1998).

60 Studies of local adaptation typically compare two or more contemporaneous populations arrayed  
61 in space across a measurable environmental gradient. Differences in allele frequencies (e.g.,  $F_{st}$ )  
62 between populations sampled from divergent environments can be used to pinpoint the genes  
63 responsible for local adaptation by finding those that deviate from the expectation of neutrality  
64 (Lewontin and Krakauer, 1973). More recently, studies of local adaptation have also sought to  
65 find correlations between genetic markers and environmental variables to better understand the  
66 connection between measures of genetic distance and the relation these have with the  
67 environment (Günther and Coop, 2013; Rellstab et al., 2015). Regardless of the approach used,  
68 these methods universally rely on the assumption that studies of local adaptation can substitute  
69 spatial distance and its correlation with environmental distance as a proxy for the operational  
70 timeframe of evolutionary dynamics in the system. This paradigm, called “space-for-time  
71 substitutions,” is not without merit, however data interpretation may be confounded by other  
72 factors such as non-equilibrium population histories, historical contingencies and genetic drift or  
73 mutation that influence the genetics of the study populations (Lovell et al., 2023; Vermeij, 2006).  
74 An approach that may ameliorate these factors would be to study a population *in situ* during  
75 evolution by sampling individuals across different points in time.

76 The availability of extended allele frequency trajectories together with contemporaneous habitat  
77 conditions affords a unique opportunity to observe evolutionary change through time. When  
78 combined together, there is the potential to develop insights in the evolution of local adaptation  
79 by the identification of underlying genetic variants responsible for phenotypic change (Weresebe  
80 and Weider, 2023). Such inference may be further heightened when considered within the  
81 context of larger spatial and temporal heterogeneity. Specifically, comparing one population  
82 experiencing significant ecological disruption to one experiencing relatively stable conditions  
83 may provide the ability to specifically account for patterns of local versus global adaptive  
84 variation. Such data can be collected for *Daphnia*, a keystone microcrustacean grazer in  
85 freshwater environments, either by direct sequencing of dormant eggs deposited in the layered  
86 sediment of lakes (Lack et al., 2018; O'Grady et al., 2022) or by sequencing the extracted DNA  
87 of 'resurrected' *Daphnia* isolates (Kerfoot et al., 1999; Kerfoot and Weider, 2004). Here we use  
88 the second approach to obtain genomic information on historic and extant populations of  
89 *Daphnia pulicaria* in two lakes located in Minnesota, USA.

90 *Daphnia* are considered keystone species in lake food webs, connecting the flow of energy from  
91 algal primary producers to higher-level consumers such as fish (Lampert, 2011). Additionally,  
92 large-bodied *Daphnia* species such as *D. pulicaria*, provision key ecosystem services including  
93 the maintenance of water clarity by reducing the standing crop of algae and supporting  
94 recreational fisheries (Walsh et al., 2016). Previous work in two lakes in Minnesota (U.S.A.),  
95 South Center (SC) Lake and Hill Lake (Frisch et al., 2014, 2017) demonstrated that since  
96 widespread Western European colonization of North America, SC Lake has experienced cultural  
97 eutrophication, transitioning to eutrophic conditions within the last 600 years with a marked shift  
98 in phosphorus conditions and lake productivity which peaked between the 1970s and 1990s  
99 (Frisch et al., 2014, 2017). In contrast, Hill Lake has not experienced strong shifts in nutrient  
100 loading, and its environmental conditions have remained relatively stable across the past ~250  
101 years (Frisch et al., 2017).

102 Extending the opening metaphor, Dickens, in a *Tale of Two Cities* highlighted the divergence of  
103 revolutionary Paris to 18th century London, a hallmark of conservative stability. Here, we utilize  
104 RADseq derived SNPs to uncover the genetic tale of local adaptation of two populations of  
105 *Daphnia pulicaria* experiencing contrasting environmental regimes. Specifically, we  
106 hypothesized that: (1) more genetic markers experience extreme changes in allele frequency over  
107 time in the population under stronger anthropogenic pressure in SC Lake compared to that of the  
108 relatively more stable Hill Lake because more drastic changes in environmental conditions  
109 would necessarily spur local adaptation; (2) the lake populations have diverging evolutionary  
110 trajectories (different gene families are impacted) due to different selection regimes; (3) genomic  
111 adaptation in each lake can be attributed to environmental history of a selection of proxies  
112 reconstructed from lake sediments.

### 113 **Methods**

#### 114 **Study area and sampling:**

115 Sediment cores were extracted from South Center (SC) Lake (45°22.645' N, 92°49.215' W) and  
116 Hill Lake (47°1.1520N, 93°5.9000W), Minnesota, USA in July 2010 and 2011. For a detailed  
117 methodology of coring and radiometric dating see Frisch et al. (2014, 2017). For this study, we  
118 isolated a total of 95 clones from lake water in 2010/2011 or resurrected them from sediment  
119 layers. In SC Lake they represent five temporal subpopulations of the years 2011, 2007, 2001,  
120 1977 (10 clones each) and 1530 (date is midpoint between two time periods that were merged -  
121 two clones from 1648 and two clones from 1418), and six temporal subpopulations in Hill Lake  
122 of the years 2010 (10 clones), 2007 (12 clones), 2002, 1997 (10 clones each), 1990 (6 clones) and  
123 1974 (date is midpoint between three time periods that were merged - one clone each from 1983,  
124 1976 and 1962). We hatched all clones from dormant eggs collected in the sediment as described  
125 in Frisch et al. (2014) except those of the years 2010 and 2011, which were directly sampled  
126 from the lake population.

127

128 **Molecular:**

129 *DNA extraction and Radseq sequencing:*

130 For each of the 95 clones, genomic DNA was extracted from 10 adult *Daphnia pulicaria* (

131 Forbes 1893) raised as isoclonal cultures, using a modified CTAB protocol (Doyle & Doyle,

132 1987). Genomic DNA was converted into nextRAD genotyping-by-sequencing libraries

133 (SNPsaurus LLC) as in Russello et al. (2015). Briefly, genomic DNA was first fragmented with

134 Nextera reagent (Illumina, Inc), which also ligates short adapter sequences to the ends of the

135 fragments. The Nextera reaction was scaled for fragmenting 2 ng of genomic DNA, although

136 2.25 ng of genomic DNA was used for input. Fragmented DNA was then amplified for 25 cycles

137 at 73 °C, with one of the primers matching the adapter and extending seven nucleotides into the

138 genomic DNA with the selective sequence GTATAGG. Thus, only fragments starting with a

139 sequence that can be hybridized by the selective sequence of the primer were efficiently

140 amplified. The nextRAD libraries were sequenced on one lane of an Illumina HiSeq 2000 to

141 generate single-end sequencing reads (University of Oregon, USA).

142

143 *Bioinformatic processing:*

144 We first de-multiplexed and quality-filtered the Illumina sequencing reads using the

145 process\_radtags command in the STACKS program (Catchen et al., 2013). We aligned the de-

146 multiplexed RAD sequencing libraries to the *Daphnia pulicaria* reference genome (Wersebe et

147 al. 2022; RefSeq: GCF\_021234035.1) using the BWA mem algorithm (Li and Durbin,

148 2009). The resulting alignments were piped to SAMtools (Li et al., 2009) to mark PCR

149 duplicates, sort the alignments and write BAM files. Next, we passed the BAM files to BCFtools

150 to call SNPs using the mpileup and call subcommands (Danecek et al., 2021). We called SNPs in

151 the data set in a population-specific manner (e.g., Hill and SC). We filtered both resulting VCF

152 files to a set of high confidence bi-allelic SNPs using BCFtools, excluding loci with a read depth  
153 <10, phred quality < 30, mapping quality < 10 and a missing rate >0.4.

154

155 *Population Structure:*

156 For each lake, we grouped samples into ‘temporal subpopulations’ based on the sediment depth  
157 from which they were hatched. We determined the approximate age of each subpopulation using  
158 the radiometric dating model (see above). We computed PCAs to evaluate the structure of  
159 temporal populations, separately for each lake. To produce the SNP set for this analysis, we  
160 pruned the set of high quality bi-allelic SNPs available for each lake for linkage disequilibrium  
161 using PLINK (Chang et al., 2015). PCAs were computed with the R package SNPrelate (Zheng  
162 et al., 2012), and visualized with ggplot2 version 3.4.2 (Wickham, 2016).

163 We further explored population genetic structure with a discriminant analysis of principle  
164 components (DAPC) with the R package adegenet version 2.1.10 (Jombart, 2008; Jombart et al.,  
165 2010). We used the function `xvalDAPC()` to estimate how many axes should be retained for the  
166 final discriminant analysis (South Center Lake: 15, Hill Lake:10).

167 PCA and DAPC were computed on the R platform version 4.2.2 (R Core Team 2022).

168

169 *Outlier Analysis:*

170 We used two methods per lake to identify outlier SNPs present in the data set. The first method,  
171 relied on the framework proposed by Wersebe and Weider (2023), which searches for SNPs with  
172  $F_{st}$  outside the neutral expectations determined by demography. As mentioned above, for each  
173 lake, we grouped samples into ‘temporal subpopulations’ based on the sediment depth from  
174 which they were hatched. We determined the approximate age of each subpopulation using the  
175 radiometric dating model (see above) and we calculated the number of generations between each  
176 subpopulation using a fixed 5 generations per year. For both lakes, the clones isolated from the  
177 water column (e.g., lake-clones) represented generation 0 with generation estimates for older

178 subpopulations relative to this benchmark. Next, we pruned the set of high quality bi-allelic  
179 SNPs available for each lake for linkage disequilibrium using PLINK (Chang et al. 2015). Using  
180 these LD-pruned SNPs, we estimated two-dimensional folded site frequency spectra (SFS) for  
181 each pairwise subpopulation comparison using the program easySFS (GitHub:  
182 <https://github.com/isaacovercast/easySFS>) formatted for the program FastSimCoal2. We fit a  
183 simple demographic scenario for each lake, where we estimated the effective population size  
184 ( $N_e$ ), a growth rate parameter and historical sampling using the observed SFS in the maximum-  
185 likelihood framework provided in FastSimCoal2. Briefly, we estimated the best fitting  
186 parameters by launching 100 independent simulations using 1-million coalescent simulations and  
187 40 Brent maximization cycles. We found the best fitting parameters by extracting the simulation  
188 run with the highest estimated likelihood from the 100 simulation runs. We conducted this  
189 process for both Hill and South Center separately. From South Center (SC) Lake we excluded  
190 the two oldest sub-populations (60-64 cm & 52-56 cm) from this analysis because the 60-64-3X  
191 clone had low overall coverage resulting in few recovered loci and the inaccuracy of estimating  
192  $F_{st}$  from small sample sizes (i.e., two clones). A similar approach was used for Hill as well,  
193 where singleton clones sampled from the oldest layers were removed.  
194 Next, we used FastSimCoal2's coalescent simulator to generate genetic markers under the  
195 inferred demographic parameters using 100 independent simulations. The SNPs simulated under  
196 the inferred demographic model were used to calculate empirical p-values for the SNPs observed  
197 in the actual populations. For each set of simulated SNPs, we converted the native FastSimCoal2  
198 format (arlequin) to VCF using PGDSpider (Lischer and Excoffier, 2012). We calculated an  
199 estimate of site-wise  $F_{st}$  in R using the package heirfstat using the function basic.stats (Goudet,  
200 2005). The simulated  $F_{st}$  values were used to construct a distribution for  $F_{st}$ -values expected  
201 under neutral demography. We tested each of the estimated  $F_{st}$  values for the observed SNPs and  
202 determined the presence of outliers by extracting SNPs with false discovery rate (FDR) corrected  
203  $F_{st}$  p-values above a  $p = 0.05$  threshold.

204

205 In addition to the simulation-based approach, we used as a second approach the outlier detection  
206 program Bayenv2 (Günther & Coop 2013) to detect SNPs potentially correlated with  
207 environmental variables inferred from the sediment cores. This program requires three input  
208 matrices that were constructed according to the Bayenv2 manual: an environmental matrix, a  
209 SNPs matrix and a covariance matrix. The environmental matrix for both lakes contained proxies  
210 for lake productivity that were estimated by paleolimnological methods using  $^{210}\text{Pb}$ -dated  
211 sediment (for details see Frisch et al. 2017): sediment age, accumulation rates (flux) of organic  
212 carbon (OC), calcium carbonates ( $\text{CaCO}_3$ ), and ortho-phosphorus (P) for both SC and Hill lakes,  
213 estimated for the 6 and 5 subpopulations in SC and Hill, respectively.

214 The covariance matrix implemented by Bayenv2 was estimated from a set of putatively neutral  
215 intergenic SNPs to account for changes in allele frequencies related to population history and  
216 sampling bias. To fit the required population covariance matrix, we extracted all intergenic SNPs  
217 present in the lake-specific and jointly called VCF files using the R packages GenomicRanges  
218 1.50.1 and GenomicFeatures 1.50.4 (Lawrence et al., 2013). Briefly, we intersected the *Daphnia*  
219 *pulicaria* RefSeq gff3 (NCBI RefSeq assembly GCF\_021234035.1) containing only gene  
220 annotations with the above described VCF file of high confidence SNPs to extract intergenic  
221 SNPs. This SNP set was then filtered using the R package SNPrelate to obtain biallelic LD  
222 pruned SNPs with a minimum allele frequency of 0.05, missing rate of 0.25, yielding 3509 SNPs  
223 for SC Lake and 2636 SNPs for Hill Lake. The covariance matrix was estimated using 500,000  
224 iterations. SNP sets for each lake were tested against the respective covariance matrix to test  
225 their correlation with the environmental matrix with 500,000 iterations and was repeated five  
226 times. We set the criteria for SNPs significantly correlated with one of the tested environmental  
227 factors as at least a median Bayes factor across the five runs of 2.0 or higher, or at least two runs  
228 with Bayes factors of 2.0 or higher.

229

230 *Power assessment and false positive rates for Bayenv2 analysis:*

231 The two sets of intergenic SNPs (one per lake) as well as the covariance matrices estimated from  
232 them were used to conduct simulations for assessing power and false positive rates of Bayenv2  
233 under different criteria. Out of all intergenic SNPs, we randomly picked 1000 SNPs to create  
234 Bayenv2 input files with a simulated environmental effect on their allele frequency. For each  
235 SNP and each population  $i$ , the empirical allele frequency was calculated by dividing the total  
236 number of chromosomes carrying the allele  $n_i$  by the total number of genotyped chromosomes  
237 for population and site  $N_i$ . Using the normalized environmental variable  $Y$  (mean 0, standard  
238 deviation 1) as well as an effect strength  $\beta$ , the simulated allele frequency  $f_i$  was calculated by  
239 adding a linear environmental effect  $\beta_i \cdot Y_i$  to the empirical point estimate  $\frac{n_i}{N_i}$  of the allele  
240 frequency. If the result fell below 0 or was greater than 1, the simulated frequency was set to 0.0  
241 or 1.0, respectively. The calculation of  $f_i$  is described in Equation (1) below.

$$f_i = \begin{cases} \text{if } \left( \frac{n_i}{N_i} + \beta \cdot Y_i \right) < 0: 0, \\ \text{if } \left( \frac{n_i}{N_i} + \beta \cdot Y_i \right) > 1: 1, \\ \text{else } \frac{n_i}{N_i} + \beta \cdot Y_i \end{cases}$$

242 Equation (1):

243 Allele counts for the Bayenv2 input files were then calculated by rounding  $f_i \cdot N_i$  to the nearest  
244 integer. The remaining chromosomes for each population were assumed to carry the alternative  
245 allele.

246 This resulted in 1000 SNPs per combination of environmental variable, effect strength  $\beta$  and test  
247 case. For each simulated SNP, Bayenv2 was then used to estimate Bayes factors with five  
248 different random seeds using the empirical covariance matrix. Two criteria were considered for  
249 the identification of outlier SNPs: a median Bayes factor across the five runs of 2.5 or higher, or  
250 at least three runs with Bayes factors of 2.0 or higher (Fig. S1 and S3 for SC Lake and Hill Lake,  
251 respectively). The estimates for the power to detect such outliers were then calculated as the

252 proportion of the simulated SNPs exceeding those criteria. Similarly, the false positive rate was  
253 estimated as the proportion of the original intergenic (i.e. presumably neutral) SNPs exceeding  
254 these criteria across five independent runs of Bayenv2 (Fig. S2 and S4 for SC Lake and Hill  
255 Lake, respectively) .

256

257 *Functional Enrichment:*

258 We sought to understand the functional context of regions hosting outlier SNPs identified with  
259 both outlier detection methods. We accomplished this by identifying enriched Gene Ontology  
260 (GO) terms for the genes related to outlier SNPs. We annotated the effects of all SNPs identified  
261 in both lakes using the program Variant Effect Predictor (VEP; (McLaren et al., 2016)), which  
262 provides both an effect of a SNP and the genes it is plausibly related to. Using this context, we  
263 were able to annotate which genes were related to the SNPs identified as outliers using the  
264 RefSeq *Daphnia pulicaria* annotation. After extracting the genes related to outlier SNPs, we  
265 annotated these genes with their PantherDB generic mappings. Using the PantherDB generic  
266 mappings for outlier-associated genes, we identified enriched GO terms via the PantherDB  
267 webtool using *Daphnia pulex* genes as a reference (Mi et al., 2021).

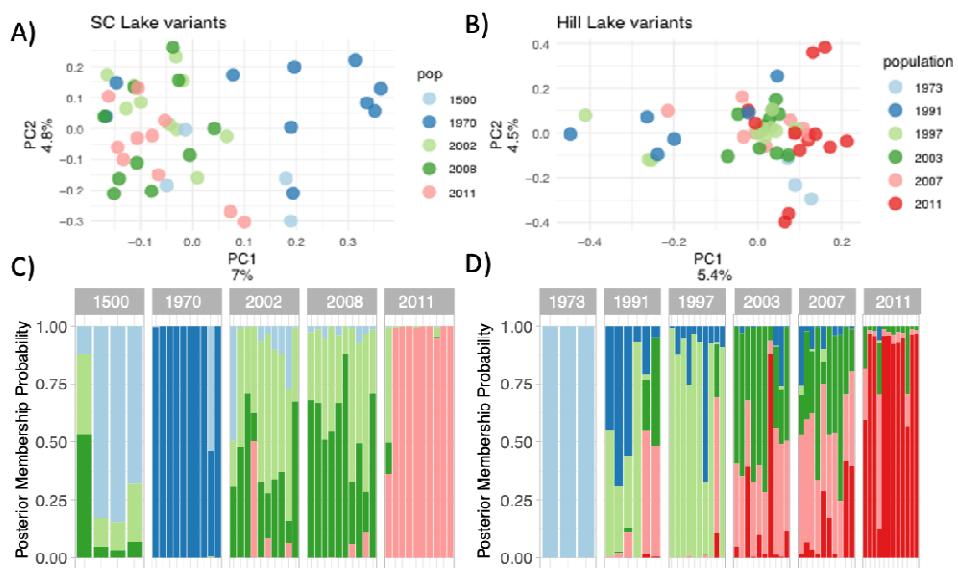
268

269 **Results:**

270 Our sequencing efforts produced 95 single-end NextRAD libraries. In total, we sequenced 44  
271 distinct clones from the South Center (SC) population and called 9505 high confidence bi-allelic  
272 SNPs from the five temporal subpopulations of this lake. We sequenced 51 samples from the six  
273 Hill temporal subpopulations, which yielded 6939 high confidence bi-allelic SNPs in the  
274 population.

275 *Population genetic structure across time:*

276 Using LD pruned SNP sets for both lakes, we computed graphic representations of PCAs and  
277 DAPCs (Fig. 1A-1C). For both lakes, the PCAs show a minor population structure with a  
278 variance between 5 and 7% on PC1, and around 5% on PC2 (Fig. 1, top panels). In SC Lake,  
279 much of this variation can be explained by the 1970 subpopulation that forms a separate cluster.  
280 In Hill Lake, none of the populations cluster distinctly from the others, and the variance is  
281 related to individuals from several temporal subpopulations. The discriminant analysis for SC  
282 resulted in distinct groupings of the subpopulations, assigning most of the individuals clearly to  
283 the sediment depth from which they were resurrected. The results of the DAPC for Hill were less  
284 distinct with mixed assignments of individuals for several subpopulations, indicating less  
285 differentiation between the Hill temporal subpopulations.



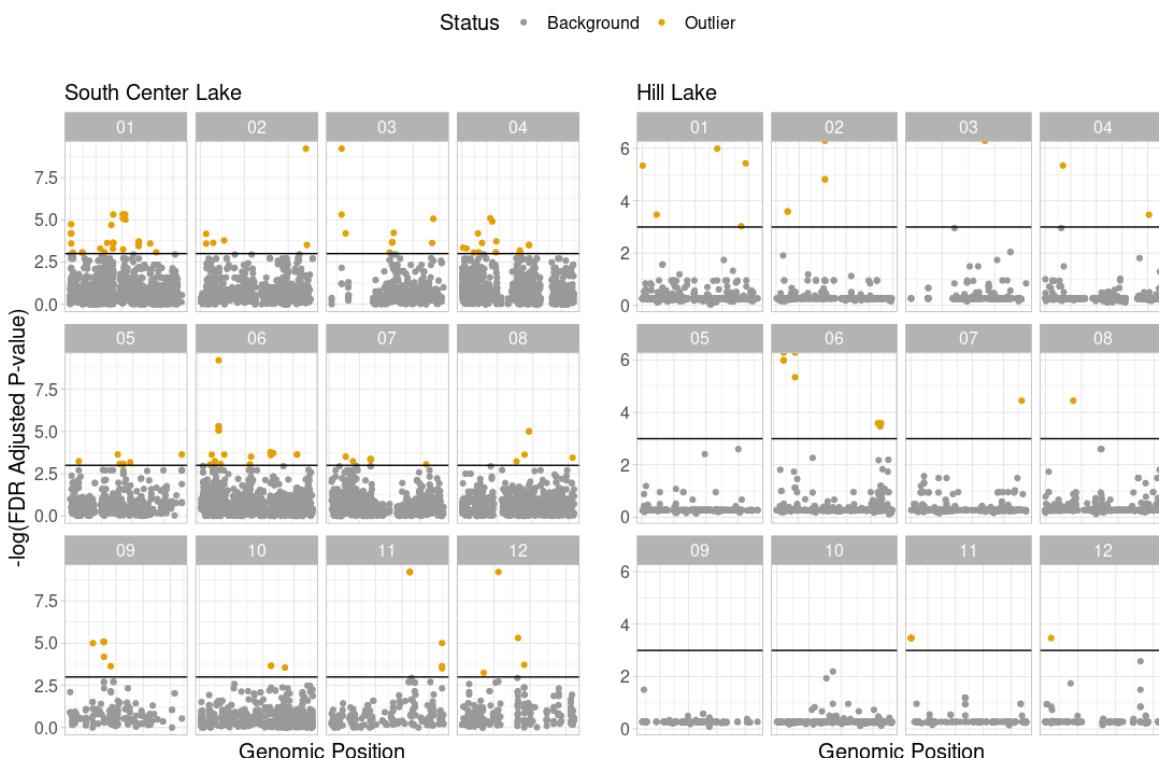
286

287 Figure 1: Population Genetic Structure. A) South Center (SC) Lake individual PCA Biplot. B)  
288 Hill Lake individual PCA Biplot. C) Discriminant Analysis of Principle Components (DAPC)  
289 posterior membership probabilities for SC Lake individuals. D) DAPC posterior membership  
290 probabilities for Hill Lake individuals.

291 *FSC Outliers:*

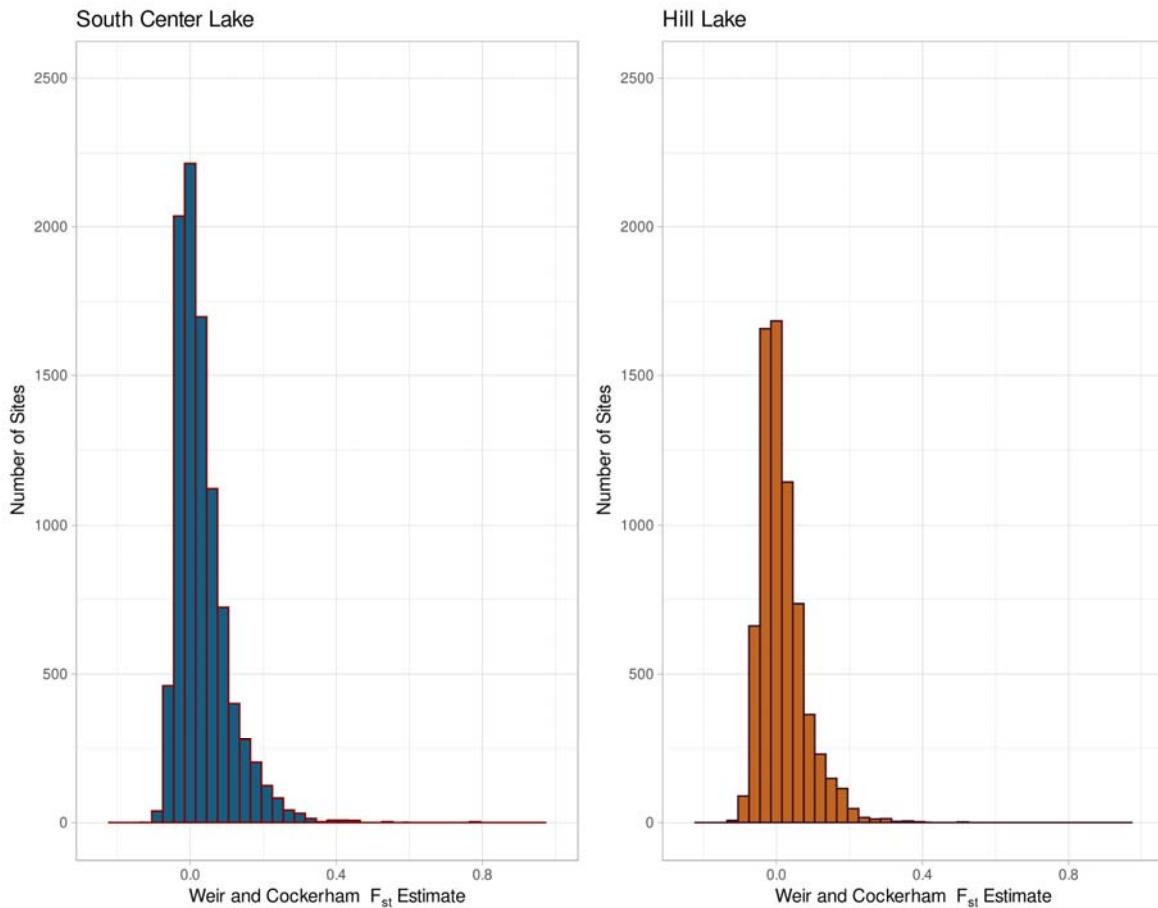
292 We estimated  $F_{st}$  for all sites recovered from the populations of each lake. We compared these  
293 against our simulated estimates for expected neutral  $F_{st}$  and estimated empirical p-values (Fig. 2-  
294 L & R). For the SC Lake population, observed  $F_{st}$  ranged from -0.1054 to a high of 0.7703 (Fig.  
295 3-L). The mean  $F_{st}$  across all sites was low overall at 0.032. In total, we identified 122 outlier  
296 SNPs with FDR adjusted p-values above a significance threshold of 0.05, these SNPs all had  $F_{st}$   
297 estimates at or above 0.2547.

298 For the Hill Lake population, the dynamics of outliers diverged significantly from those  
299 observed in the SC population. Observed site-wise estimates of  $F_{st}$  ranged from a low of -0.1219  
300 to a high of 0.519 (Fig. 3-R). The mean  $F_{st}$  across the subpopulations was also relatively low at  
301 0.016. In total, however, we observed just 29 outlier loci in the entire data set, all of which had  
302 estimated  $F_{st}$  at or above 0.2839.



304 Figure 2:  $F_{st}$  outliers. Left)  $F_{st}$  outliers identified in South Center (SC) Lake. Right)  $F_{st}$  outliers  
305 identified in Hill Lake. Grey points are SNPs without significant  $F_{st}$  values based on simulation

306 Gold points are SNPs with significant  $F_{st}$  values based on simulations. Vertical bars denote  $p =$   
307 0.05 cutoff.



309 Figure 3) Observed  $F_{st}$  distribution. Left) South Center (SC) Lake. Several sites reach  $F_{st}$  near  
310 0.77. Right) Hill Lake.  $F_{st}$  reaches a high of 0.55.

311

312 *Functional Enrichment:*

313 To better understand the genomic context of outlier regions, we extracted the genes related to  
314 high  $F_{st}$  SNPs and annotated them with Gene Ontology (GO) terms.

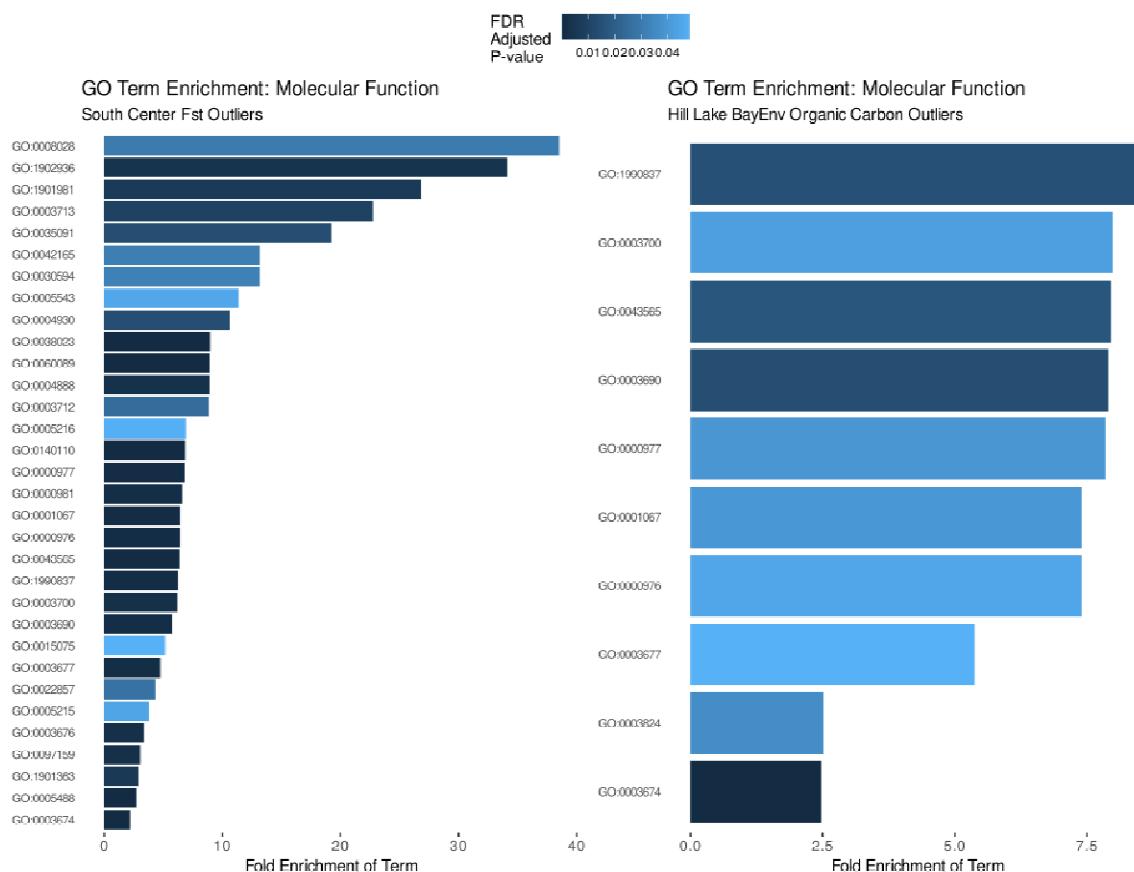
315  $F_{st}$  Outliers:

316 We extracted a total of 120 unique genes that were related to high  $F_{st}$  SNPs identified in the SC  
317 population. We were able to annotate 118 of these genes with functional family information  
318 while searching against the Panther database. This list of genes yielded 32 GO terms for  
319 Molecular Function that appeared enriched after using a Fisher exact test against the *Daphnia*  
320 *pulex* gene list available on PantherDB webtool and correcting for FDR. Enriched GO terms  
321 were related to several molecular functions; however, transmembrane transport proteins for both  
322 organic molecules and ions and molecule-specific binding made up many of the enriched terms.  
323 Meanwhile, for the Hill Lake population, we only identified 24 genes related to outlier SNPs.  
324 This yielded no enriched terms for molecular function, and the gene list contained only two  
325 genes that were found in South Center.

326 Bayenv2 Outliers:

327 We identified only five outlier loci in the SC population, which were related to six genes. This  
328 relatively small number reflects the low power of Bayenv2 to detect environmental outliers in  
329 South Center (Fig. S1 and S3), likely originating from the strong correlation between the main  
330 axis of population structure (Fig 1A) and the environmental variables which caused Bayenv2 to  
331 over-correct for this structure. The six genes resulted in no enriched GO terms for molecular  
332 function. The Hill population had loci correlated with age,  $\text{CaCO}_3$ , Organic Carbon (OrgC) and  
333 phosphorus (P) ranging from a high of 43 loci correlated with OrgC content to 5 loci correlated  
334 with P (Table S1). The small number of genes related to outlier SNPs from age, P, and  $\text{CaCO}_3$   
335 did not result in any enriched GO terms. However, SNPs associated with organic carbon were  
336 related to a total of 58 genes. This gene list resulted in 10 enriched GO terms which were related  
337 to several transcription factors including binding and regulation.

338



339

340 Figure 4) Outlier SNP GO term Enrichment. Left) PANTHERDB GO term for molecular  
341 function enriched among  $F_{st}$  outlier SNPs identified in SC Lake. Right) PANTHERDB GO term  
342 for molecular function enriched among Bayenv outlier SNPs identified in Hill Lake. The GO  
343 terms corresponding to IDs here are present in tables S2 (L) and S3 (R).

#### 344 **Discussion:**

345 Our data support our first hypothesis - that significant anthropogenic changes within a lakes'  
346 watershed would result in more genetic markers experiencing dramatic changes in allele  
347 frequency. We found only limited support for our other two hypotheses that lake populations  
348 would have diverging evolutionary trajectories related to different selection regimes and that  
349 genomic adaptation can be attributed to selected environmental proxies. In many cases, similar  
350 GO terms for molecular function were enriched in both lakes and few SNPs had measurable  
351 gene-environment correlations.

352 **Human impacts leave measurable signatures in the genome:**

353 The identification of  $F_{st}$  outliers revealed more than four times the number of outliers in SC Lake  
354 compared to those observed in Hill Lake (i.e., 122 sites vs 29 sites). This supports our hypothesis  
355 that more sites would be under selection in the *Daphnia* population of SC Lake, resulting from  
356 the dramatic environmental changes in this lake. The SC lake watershed is dominated largely by  
357 pastureland and row-crop agriculture encompassing 38% and 23% of the watershed area,  
358 respectively (MNPACA, 2009a). As noted previously (Frisch et al. 2014, 2017) this has created a  
359 set of novel environmental conditions in SC Lake, particularly because of nutrient loading (N &  
360 P) from agricultural run-off. The watershed of Hill Lake, by contrast, is largely dominated by  
361 forest covering approximately 75% of the watershed whereas 14% of the land is used by  
362 agriculture resulting in mesotrophic conditions (MNPACA, 2009b). This provides further evidence  
363 of the enormous adaptive capacity of *Daphnia* populations at the genomic level. Previous studies  
364 have shown that resurrected individuals from the SC population have evolved phenotypic  
365 plasticity in their phosphorus (P) physiology that allows them to regulate the retention of P  
366 according to availability in the environment (Frisch et al., 2014; Chowdhury and Jeyasingh,  
367 2016; Frisch et al., 2020). Other resurrection studies have shown an adaptive capacity to a  
368 variety of environmental challenges including salt pollution (Wersebe and Weider 2023) or  
369 rising temperatures (Geerts et al 2015). This suggests that *Daphnia* populations will continue to  
370 support aquatic food webs and maintain the ecosystem services they provide (Walsh et al. 2016)  
371 as long as the pace or strength of environmental stress does not overwhelm their adaptive  
372 capacity.

373 **Many SNPs, no coherent genes:**

374 Our results from the SC population  $F_{st}$ -tests are congruent with other recent studies which have  
375 used resurrection ecology paired with genome-wide markers to study local adaptation. Both  
376 Chaturvedi et al. (2021) and Wersebe and Weider (2023) found that a large number of SNPs may

377 rapidly change in allele frequency in *Daphnia* populations experiencing novel environmental  
378 conditions. However, these studies employed whole-genome sequencing to identify SNPs  
379 segregating in the study populations over time. For example, Wersebe and Weider (2023) were  
380 able to use their data set to identify genes and mutations with known functions that were related  
381 to the physiology of the trait (i.e., salinity tolerance) they suspected to be under selection in the  
382 study population. In contrast, Chaturvedi et al. (2021) did not attempt to identify the genes or  
383 functional implications of the SNPs detected in their study.

384 Here, our effort to identify genes associated with the  $F_{ST}$ -outlier SNPs did not reveal distinct  
385 physiological functions that might be plausibly related to eutrophication. For instance Weider et  
386 al. (1997), proposed that allozyme variation at the phosphoglucose isomerase (PGI, EC 5.3.1.9)  
387 gene was related to micro-evolutionary changes associated with eutrophication in the Lake  
388 Constance (Bodensee, Germany) *Daphnia* population. Further experimental work has suggested  
389 that PGI-genotype may indeed play a role in the competitive ability of *Daphnia* under  
390 contrasting phosphorus supply (Jeyasingh et al., 2009). Despite the lack of a single locus of large  
391 effect with a clear physiological connection, we did find similar sets of genes enriched as those  
392 detected by Muñoz et al. (2016). These authors analyzed SNPs detected with genotype-by-  
393 sequencing from several *Daphnia pulicaria* populations in Minnesota including SC and Hill  
394 Lakes.

395 Many of the outlier SNPs detected here were enriched in GO terms related to regulation of  
396 transcription, but not immediately connected to nutrient physiology. The lack of a coherent list  
397 of genes may be related to several factors. We employed a variant of RADseq which is known as  
398 a reduced representation method. RAD genotyping only samples loci in the genome near enzyme  
399 cut sites and as a result, only samples a small portion of the DNA (Andrews et al., 2016). Some  
400 have questioned this method for studying local adaptation (Lowry et al., 2016), because the RAD  
401 approach lacks sufficient marker density to sample sites in tight linkage disequilibrium with a  
402 selected site. As such, we may have lost some power to detect selection in the genome.

403 Furthermore, since coverage is restricted to RAD tags, we were unable to search regions  
404 surrounding outliers for SNPs within genes causing missense mutations or premature stop  
405 codons. Such non-neutral variation is the target of selection, which might narrow a list of nearby  
406 candidate genes when examined more closely.

407 **Paleo-environmental correlations with allele frequency change:**

408 While the  $F_{st}$  analysis supported our hypothesis, the Bayenv analysis did not produce congruent  
409 results. This analysis detected most outlier SNPs in the Hill Lake population, while a much lower  
410 number was found in the SC Lake population. As demonstrated by the Bayenv simulations (Fig.  
411 S1,S2,S3, S4), the power of detecting outlier loci in SC Lake was very low due to the strong  
412 correlation between variation in the SNP data and environmental variables. While Bayenv2 is  
413 designed to avoid false positives due to background population structure, it might over-correct if  
414 the population structure is highly correlated with the environmental variables reducing the  
415 chances of finding loci involved in environmental adaptation. This strong correlation between  
416 genomic and environmental variation across time might explain why more SNPs with high  $F_{st}$   
417 could be detected when applying an  $F_{st}$  approach without considering environmental data.

418 For Hill Lake, this correlation was less pronounced, allowing a greater power of detecting  
419 outliers associated with environmental variables. In this lake, the only environmental factor with  
420 many correlated outliers was organic carbon (OrgC) flux. This OrgC paleo-environmental record  
421 tracks the burial of organic matter in lake sediments (Tranvik et al., 2009). Studies of Minnesota  
422 Lakes have revealed that one of the primary controls of lake OrgC burial is a change in land use  
423 within a lake's watershed (Anderson et al., 2013). As noted previously, land use is strikingly  
424 different between Hill and South Center, with the most dramatic changes occurring within South  
425 Center Lake's watershed. These results remain difficult to explain in the context of the data we  
426 collected.

427 There are several factors that might impact studies such as ours, many of them inherent with  
428 difficulties related to the design of resurrection ecology studies. Our sampling of individuals  
429 throughout the core relies solely on *Daphnia pulicaria* lineages that hatched and survived in  
430 laboratory culture. This may have resulted in a non-representative sampling consisting of those  
431 genotypes that survived extended diapause and laboratory conditions. This produces a bias  
432 termed the “invisible fraction”, which arises when strong correlations exist between propagule  
433 survival and traits of interest for a given genotype (Weis, 2018). However, such biases are not  
434 directly quantifiable without knowledge of the ancestral relationships of hatched propagules. In  
435 previous studies (Frisch et al. 2014, 2017), the sampling design would have alleviated the impact  
436 of the invisible fraction because eggs were recovered from the sediments and genotyped directly.  
437 These studies demonstrated compelling evidence of gene-environment correlations, which we  
438 did not recover despite the larger number of markers employed in the present study. The larger  
439 number of sampled haplotypes in these studies may have improved the ability to detect allele  
440 frequency shifts which underly the reported gene-environment correlations.

441 Frisch et al. (2014) also observed phenotypic changes in the SC Lake population after profiling  
442 some of the clones included in this present study for phosphorus use efficiency and growth rate  
443 (e.g., fitness) under contrasting nutrient conditions. These observations may be related to  
444 transcriptomic and/or epigenomic changes across time rather than selection on genetic variation  
445 in the genes underlying physiological traits. Further, Frisch et al. (2020) mapped the  
446 transcriptional networks associated with P-use traits in the SC population. While many  
447 transcriptional responses were shared between the ancient and modern clones profiled, a small  
448 number showed novelty in the modern clones under P-limitation. Such a mechanism might  
449 explain in part why here, we uncovered several genes related to regulation and translation rather  
450 than to nutrient physiology. This highlights the importance of designing studies that incorporate  
451 the full complement of functional genomic interrogation including full genome sequences,  
452 transcriptomic and epigenomic profiles and common garden experiments to understand the

453 genetic basis of phenotypic change in wild populations. Such a comprehensive and multi-faceted  
454 study using the resurrection approach has yet to be conducted.

455

456 **Challenges and Considerations of the “resurrection” approach:**

457 Many studies utilizing the resurrection approach consider the evolutionary trajectory of a single  
458 lake and its target population (see Weider et al. 2018 for an overall review). While this approach  
459 may be powerful, results from a single population are inherently phenomenological without  
460 replication or control. The addition of a “control” population such Hill Lake in our study allows  
461 us to demonstrate a concerted change in South Center Lake. However, there are several  
462 challenges and considerations that any chosen design introduces that complicate a direct  
463 comparison. Specifically, it is important to have sufficient sample sizes across time periods and  
464 lakes to make temporal comparisons meaningful. One of the primary differences between our  
465 analytical approaches was whether the oldest clones recovered were included in the results.  
466 Since it is difficult to accurately determine allele frequencies from such small sample sizes, we  
467 opted not to include these in the  $F_{st}$ -based analysis. However, they were included in the Bayenv  
468 analysis. This may explain in part the contrasting results of these approaches but more  
469 importantly it also highlights the importance of acquiring a large enough sample size from each  
470 temporal subpopulation. Additionally, to allow for a meaningful comparison between two or  
471 more lakes, populations should be sampled on the same temporal scale. With the exclusion of the  
472 oldest samples from both lakes, our data sets spanned a similar timeframe (30 years in SC Lake,  
473 20 years in Hill Lake), but the Hill Lake core was more densely sampled compared to the SC  
474 Lake core. This has unknown effects on the inference that can be gleaned from the data.

475 **Conclusions:**

476 The South Center and Hill populations tell a tale that spans decades to centuries. However, the  
477 genes in these populations are not easy to read. Ultimately, the *Daphnia pulicaria* populations in  
478 each lake show distinct patterns of adaptation, which coincide with many more  $F_{st}$  outliers in the  
479 SC Lake population than in Hill Lake. Most outlier SNPs are related to transcriptomic  
480 modification and regulatory genes suggesting that adaptation in these lakes is related to a  
481 complex molecular rewiring rather than one or a few major-effect genes with known  
482 physiological function. However, when conducting resurrection studies, we recommend that care  
483 and attention be paid to sample size. This can help to increase the likelihood that the analyses  
484 produce meaningful results. This is a challenge inherent in resurrection ecology because  
485 idiosyncratic deposition and preservation of eggs within sediment cores are ultimately  
486 unknowable before selecting lakes and the temporal resolution of ephippial sampling. Regardless  
487 of current limitations, the further refinement of resurrection ecological studies has the potential  
488 to provide a powerful means of examining temporal genome-environment interactions that can  
489 complement space-for-time studies (Weider et al., 2018)

490

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508

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510 DF and PKM performed initial isolation and sequencing. DF and MJW performed analysis and  
511 wrote the first draft. TG contributed analysis and support for the Bayesian outlier detection. LJW  
512 provided funding and administration. All authors contributed to editing and reviewing the final  
513 draft.

514

515 **Data availability:**

516 All data and custom scripts will be archived on Dryad upon acceptance of this paper. Sequencing  
517 reads will be made available via NCBI's SRA upon acceptance.

518

519 **Conflict of Interests:**

520 Authors declare no conflicts of interest.

521

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