

Genomics versus mtDNA for resolving stock structure in the silky shark (*Carcharhinus falciformis*)

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Conservation genetic approaches for elasmobranchs have focused on regions of the mitochondrial genome or a handful of nuclear microsatellites. High-throughput sequencing offers a powerful alternative for examining population structure using many loci distributed across the nuclear and mitochondrial genomes. These single nucleotide polymorphisms are expected to provide finer scale and more accurate population level data; however, there have been few genomic studies applied to elasmobranch species. The desire to apply next-generation sequencing approaches is often tempered by the costs, which can be offset by pooling specimens prior to sequencing (pool-seq). In this study, we assess the utility of pool-seq by applying this method to the same individual silky sharks, *Carcharhinus falciformis*, previously surveyed with the mtDNA control region in the Atlantic and Indian Oceans. Pool-seq methods were able to recover the entire mitochondrial genome as well as thousands of nuclear markers. This volume of sequence data enabled the detection of population structure between regions of the Atlantic Ocean populations, undetected in the previous study (inter-Atlantic mitochondrial SNPs F_{ST} values comparison ranging from 0.029 to 0.135 and nuclear SNPs from 0.015 to 0.025). Our results reinforce the conclusion that sampling the mitochondrial control region alone may fail to detect fine-scale population structure, and additional sampling across the genome may increase resolution for some species. Additionally, this study shows that the costs of analyzing 4,988 loci using pool-seq methods are equivalent to the standard Sanger-sequenced markers and become less expensive when large numbers of individuals (>300) are analyzed.

1 **Genomics versus mtDNA for Resolving Stock Structure in the Silky Shark**
2 **(*Carcharhinus falciformis*)**

3

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26 Abstract

27 Conservation genetic approaches for elasmobranchs have focused on regions of the
28 mitochondrial genome or a handful of nuclear microsatellites. High-throughput sequencing
29 offers a powerful alternative for examining population structure using many loci distributed
30 across the nuclear and mitochondrial genomes. These single nucleotide polymorphisms are
31 expected to provide finer scale and more accurate population level data; however, there have
32 been few genomic studies applied to elasmobranch species. The desire to apply next-generation
33 sequencing approaches is often tempered by the costs, which can be offset by pooling specimens
34 prior to sequencing (pool-seq). In this study, we assess the utility of pool-seq by applying this
35 method to the same individual silky sharks, *Carcharhinus falciformis*, previously surveyed with
36 the mtDNA control region in the Atlantic and Indian Oceans. Pool-seq methods were able to
37 recover the entire mitochondrial genome as well as thousands of nuclear markers. This volume
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39 Ocean populations, undetected in the previous study (inter-Atlantic mitochondrial SNPs F_{ST}
40 values comparison ranging from 0.029 to 0.135 and nuclear SNPs from 0.015 to 0.025). Our
41 results reinforce the conclusion that sampling the mitochondrial control region alone may fail to
42 detect fine-scale population structure, and additional sampling across the genome may increase
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44 using pool-seq methods are equivalent to the standard Sanger-sequenced markers and become
45 less expensive when large numbers of individuals (>300) are analyzed.

46

47 Introduction

48 Many elasmobranchs around the globe have experienced devastating population declines due to
49 overfishing in both target and non-target fisheries (Musick et al., 2000; Clarke et al., 2006; F.
50 Ferretti et al., 2010; Heupel et al., 2014; Dulvy et al., 2014; Oliver et al., 2015; Dulvy &
51 Trebilco, 2018). These species are especially vulnerable to overfishing due to life history traits
52 such as late maturity, slow growth, low fecundity, and high juvenile mortality, which collectively
53 result in low intrinsic rate of population increase (Baum et al., 2003; Dulvy et al., 2008).
54 Elasmobranch populations take decades to recover from overfishing, and only if fishing pressure
55 is relieved for an extended period (Stevens et al., 2000). Furthermore, many threatened and
56 endangered elasmobranchs have little to no population genetic data that would assist in the
57 resolution of management units (reviewed in Domingues et al., 2018a).

58

59 Genetically distinct populations are isolated management units known as stocks; however, stocks
60 can be defined on a smaller scale than genetic populations through other criteria, such as an
61 exclusive economic zone boundary (Carvalho & Hauser, 1994; Ovenden et al., 2015). Reduced
62 gene flow indicates that if a population is overfished it will not be replenished by immigrants
63 from surrounding populations. This is why managing on a genetic stock-by-stock basis is
64 essential for successful maintenance of exploited species and is sorely needed for over-harvested
65 elasmobranchs (Dizon et al., 1993; Heist, 2004; Tallmon et al., 2010).

66

67 For the past two decades the standard for examining population structure in elasmobranchs has
68 been a section of the mitochondrial genome, usually the control region (mtCR) (e.g. Duncan et
69 al. 2006; Hoelzel et al. 2006; Keeney & Heist 2006; Castro et al. 2007; Whitney et al. 2012;
70 Clarke et al. 2015; reviewed in Domingues et al. 2018a). Though recent studies are moving

71 towards multi-marker approaches (Momigliano et al., 2017; Pazmiño et al., 2018; Green et al.,
72 2019), there is still a large body of literature focusing on mtCR. The mitochondrial genome has a
73 higher rate of mutation than most of the nuclear genome (Brown et al., 1979; Charlesworth &
74 Wright, 2001; Neiman & Taylor, 2009) and this rate of mutation is a key advantage in
75 vertebrates with slowly-evolving genomes (Awise et al., 1992; Martin et al., 1992).

76 Elasmobranch mtDNA studies to date have been successful in elucidating population partitions
77 and evolutionary divergences, but the maternal inheritance of mtDNA can limit conclusions
78 about gene flow in cases of sex-biased (usually male) dispersal. Both mtDNA and nuclear
79 markers often have concordant results in sedentary species (e.g., Lavery et al., 1996; Avise,
80 2004; Zink & Barrowclough, 2008; DiBattista et al., 2015) but, when examined alone, may miss
81 key components of population structure, particularly in migratory fauna (Pardini et al., 2001;
82 Bowen et al., 2005; Toews & Brelsford, 2012). When highly mobile elasmobranchs are
83 examined with both mtDNA and nuclear markers (usually microsatellites), a different picture
84 often emerges in which females are more resident and males are dispersive (Pardini et al., 2001;
85 Schultz et al., 2008; Portnoy, et al., 2010; Karl, Castro, Lopez, Charvet, & Burgess, 2011; Daly-
86 Engel et al., 2012; Portnoy et al., 2015; Bernard et al., 2017; Domingues et al., 2018b).

87 Identifying outlier SNPs in the nuclear genome can highlight genes possibly under selection, or
88 show functional responses to environmental changes that have important management
89 consequences (Barrio et al., 2016; Fischer et al., 2013; Guo et al., 2016; Jones et al., 2012).

90 Therefore, the combination of mitochondrial and nuclear markers can yield fundamental
91 ecological and evolutionary insights.

92

93 High-throughput sequencing is a powerful tool for revealing fine-scale population structure that
94 may be missed by single locus studies (Andrews et al., 2016; Hohenlohe et al., 2018). However,
95 this method can be costly, especially when examining many individuals as is typical of
96 population genetic or phylogeography studies, and the perceived cost may prevent some from
97 considering a high-throughput sequencing approach. For population genetics approaches based
98 on differences in allele frequencies among populations, equimolar pooling of samples before
99 sequencing is an affordable and accurate strategy for large-scale genetic analysis (Schlötterer et
100 al., 2014). Several studies have successfully resolved population structure using a pooled site-
101 associated DNA approach known as pool-seq, including some in commercially valuable marine
102 species (e.g. Gautier et al., 2013; Mimee et al., 2015). Pool-seq provides estimates of allele
103 frequencies for thousands of loci distributed across the genome simultaneously, which in some
104 cases gives greater statistical power that can actually exceed the accuracy of allele frequency
105 estimates based on individual sequencing (Futschik & Schlötterer, 2010, but also see Anderson
106 et al. 2014). Therefore, a comparison of results between the standard mtCR analysis and high-
107 throughput pool-seq is informative in evaluating the relative power and cost of the two
108 approaches for examining population structure.

109

110 The silky shark (*Carcharhinus falciformis* (Müller & Henle, 1839)) is the second most
111 commonly harvested shark on Earth (Oliver et al., 2015; Rice & Harley, 2013). They are one of
112 the top contributors to the shark fin trade and the most common elasmobranch bycatch species in
113 tuna purse-seine fisheries around the world (Cardenosa et al., 2018; Clarke et al., 2006; Oliver et
114 al., 2015). This pelagic shark, formerly abundant in all tropical oceans, has declined by an
115 estimated 85% in the last 20 years, and is now listed as vulnerable and declining by the

116 International Union for the Conservation of Nature (Rice & Harley, 2013; IUCN, 2017).
117 Currently silky shark population assessments are conducted at the scale of regional fishery
118 management organization, and conservation management measures are implemented at this scale
119 in the absence of genetic or movement data to define population boundaries. Clarke et al. (2015)
120 surveyed silky sharks across these regional management regions and found the western Atlantic
121 was strongly differentiated from the Indian Ocean, but the North Atlantic, Gulf of Mexico, and
122 Brazil could not be differentiated and appeared to comprise a single population. In contrast,
123 using the same mtCR marker, Domingues et al. (2017) examined five regions across the Western
124 Atlantic and found the North Western Atlantic was distinct from the South Western Atlantic. The
125 difference between the two studies results from additional sampling in the South West Atlantic
126 from further south than Clarke et al. (2015).

127

128 In an era where wildlife management needs far exceed the financial resources to address them,
129 many seek to find the most accessible, robust, and economical means to define management
130 units. In this study, we provide a direct comparison of population genetic analysis methods
131 between Sanger sequencing of the mtCR region and high-throughput sequencing of regional
132 pools of individuals. The same individuals from Clarke et al. (2015) were re-sequenced using
133 pool-seq approaches. Regions re-sequenced included Gulf of Mexico, North West Atlantic, and
134 Brazil, as well as one geographically distant location in the Red Sea (*Fig 1*). We focused this
135 analysis on SNPs from the mitochondrial DNA as well as nuclear DNA. We did not analyze any
136 microsatellite loci because they were not a part of Clarke et al. (2015). We then evaluate the
137 economics of conducting pool-seq relative to conventional Sanger sequencing of these same

138 individuals. Ecological and management implications will be addressed in a subsequent
139 companion paper.

140

141 **Materials & Methods**

142 *Sampling and sequencing*

143 A total of 143 silky shark fin clips or muscle sections were sampled from commercial or artisanal
144 fisheries across four geographic regions and are the same samples examined in Clarke et al.
145 (2015). Specifically, we sampled the Gulf of Mexico (GM, n =39), the North Atlantic (NA, n =
146 33), Brazil (BR, n = 34), and the Red Sea (RS, n = 37). These sample sizes are slightly lower
147 than Clarke et al. (2015). This reduction was due to DNA degradation over time and the need for
148 high-quality genomic DNA for pool-seq. This is contrary to the DNA quality needed for
149 amplifying a single marker from the mitochondrial control region. Additionally only a subset of
150 the Red Sea samples were randomly selected to keep sample sizes relatively similar.

151

152 DNA was extracted using Qiagen DNeasy Blood & Tissue kit (Qiagen, Mississauga, ON,
153 Canada), following manufacturer protocols. Extracted DNA quality was assessed visually by gel
154 electrophoresis and imaged using Gel Doc E-Z System (BIO RAD, Hercules, California, USA).
155 Only DNA aliquots with strong genomic DNA bands were further processed, while degraded or
156 overly digested DNA was discarded. Aliquots of high-quality DNA were quantified using an
157 AccuClear Ultra high sensitivity dsDNA quantitation kit (Biotium, Fremont CA, USA) and a
158 SpectroMax M2 (Molecular Devices, Sunnyvale, CA, USA). Libraries were pooled with an
159 equal amount of DNA (ng/μl) contributed per individual to minimize individual contribution
160 bias, totaling 2000 ng of DNA per library. Number of individuals per pool are displayed in *Fig 1*.

161 No PCR was performed to ensure individual DNA contribution was kept equal within and across
162 libraries (Anderson et al., 2014). The rest of the library preparation followed the ezRAD library
163 preparation protocol (Toonen et al. 2013; Knapp et al., 2016). This included DNA digested with
164 DpnII restriction enzyme and adapters ligated using a Kapa hyper Prep Kit (Kapa Biosystems,
165 Wilmington, MA, USA). Pooled libraries were sequenced using Illumina MiSeq (v3 2x300bp
166 PE) at the Hawai'i Institute of Marine Biology EPSCoR Core sequencing facility.

167 *Genetic analyses*

168 MultiQC was used to assess sequence quality scores, sequence length distributions, duplication
169 levels, and overrepresented sequences (Ewels et al., 2016). To analyze the mitochondrial
170 genome, a previously published mitochondrial genome from *Carcharhinus falciformis* was used
171 as a reference (GeneBank accession number KF801102). Raw paired-end reads were trimmed
172 with TRIMMOMATIC, mapped to the mitochondrial genome reference BWA (mem algorithm),
173 and variants called using the dDocent bioinformatics pipeline, modified for pool-seq (Puritz et al.
174 2014, see below for details). Called SNPs were then analyzed with AssessPool
175 (github.com/ToBoDev/assessPool, see below for details).

176

177 The bioinformatics pipeline included dDocent followed by AssessPool. Given that no reference
178 genome was available, a reference was constructed using the dDocent *de novo* assembly and
179 optimized utilizing the reference optimization steps provided on the dDocent assembly tutorial
180 (<http://ddocent.com/assembly/>). Before assembly reads were trimmed using default settings and
181 then an overlap (OL) assembly was performed, followed by clustering with CD-HIT with a $-c$
182 parameter of 90% similarity. For mapping using BWA (mem algorithm) all match, mismatch,
183 and gap open penalty score parameters were also default settings. Different parameters were

184 tested during optimization but did not improve mapping. Within-pool (K1) and between-pool
185 (K2) minimum locus depth values selected for the *de novo* assembly did impact the results.
186 dDocent provides graphical outputs to help select these values; however, testing a few different
187 values of each is recommended to fully explore the potential of the data by balancing number of
188 contigs by coverage depth (see ddocent.com/UserGuide for details). Selected values for K1 and
189 K2 were 3 and 3 respectively. Once assembled, sequences were mapped, SNPs were called
190 within the dDocent pipeline using FreeBayes, modified for SNP calling in pools (Garrison and
191 Marth 2012, <https://github.com/ekg/freebayes>). Any contigs that aligned to the mitochondrial
192 genome were removed from this nuclear dataset. The contigs that aligned specifically to the
193 mitochondrial control region were saved for SNP validation to directly compare the results from
194 this pool-seq approach to those previously reported by Clarke et al. (2015).
195
196 SNP calling with FreeBayes was optimized for pooled samples using the ‘pooled-continuous’
197 option, and minor allele frequency was decreased to 0.05 to capture alleles with frequency
198 greater than 5% in the population (See Supplementary Material for code). The dDocent pipeline
199 outputs SNPs in two variant call format files (.vcf), one being all raw SNPs (TotalRawSNPs.vcf)
200 and another with filtered SNPs (Final.recode.vcf) however dDocent does not optimize filtering
201 for pool-seq data. Therefore, the raw SNPs were processed with the pool-seq specific program
202 AssessPool which uses VCFtools and vcflib to filter SNPs (Danecek et al., 2011). SNPs were
203 processed with the following filters: minimum pool number of 2, minimum quality score of 20,
204 minimum depth threshold of 30, maximum amount of missing data of 3, maximum allele length
205 of 10, quality score to depth ratio of 0.25 as well as mean depth per site vs. quality score, and
206 finally a maximum mean depth threshold of 1000 (*Table S1*). AssessPool then sends filtered

207 SNPs to either PoPoolation2 (Kofler et al., 2011) or poolfstat (Hivert et al., 2018). PoPoolation2
208 calculates mean pairwise F_{ST} values and significance in the form of p-values obtained using
209 Fisher's exact test and combined using Fisher's method (as described in Ryman et al. 2006).
210 Poolfstat (Hivert et al. 2018) takes a different approach, calculating F_{ST} values based on an
211 analysis-of-variance framework (*sensu* Wier & Cockerham 1984) to eliminate biases associated
212 with varying pool sizes. AssessPool then organizes, summarizes, and creates visualizations of the
213 data using RStudio (RStudio Team 2020).

214

215 As a quality control test, sequences from Clarke et al. (2015) were downloaded from GenBank
216 (accession numbers KM267565–KM267626), and SNPs from these data were compared directly
217 to SNPs called within the control region of the mitochondrial pool-seq data generated here.
218 Concordance of this validation set of SNPs was determined by Mantel test in R (Legendre &
219 Legendre, 1998) comparing the matrices of pairwise F_{ST} values among populations.

220 ***Cost Analysis***

221 The cost of pool-seq approach compared to Sanger sequencing of individual loci was calculated
222 based on library preparation and sequencing cost at our facility. We did not include labor but
223 calculated the total cost to generate sequence data from each sample included here from such
224 expenses as the extraction, laboratory consumables, PCR amplification, library preparation,
225 reaction clean-ups, quantification, quality control testing, and sequencing costs. These costs were
226 translated into functions in RStudio (RStudio Team, 2020) where Sanger sequencing is a fixed
227 rate per individual and pool-seq costs are fixed per flow cell on our MiSeq, but individual cost
228 varies based on number of individuals and number of pooled regions per sequencing run. These
229 functions were then plotted together for comparison.

230

231 **Results**

232 A total of 30.8 million reads were generated for the four geographic regions, which averaged 7.7
233 \pm 3.0 million reads per pooled library. Results from the MutliQC assessment showed fairly
234 homogenous output between libraries in regard to sequence quality scores, GC and per base
235 sequence content, sequence length distributions, duplication levels, overrepresented sequences,
236 and adapter content. Once assembled, aligned, and mapped, 5,792 SNPs were resolved across the
237 mitochondrial and nuclear genomes combined. There were 4,103 biallelic SNPs, 168 were
238 multiallelic SNPs and 48 were insertions and deletions (INDELs). INDELs and multiallelic
239 SNPs remain a challenge for quantification software, so we restricted our analysis to biallelic
240 loci (Fracassetti et al. 2015). AssessPool creates visualizations of F_{ST} values and allows for visual
241 outlier inspection. No visual outliers were present and given these SNPs are distributed
242 haphazardly across the genome, they are assumed to be putatively neutral.

243

244 ***Mitochondrial Genome***

245 Analysis of the complete mitochondrial genome (17,774 bp) revealed 804 variable sites: 681
246 biallelic and 17 multiallelic SNPs. Because coverage in this dataset was fairly low on average,
247 most of these SNPs did not meet the filter threshold. After further filtering for the highest quality
248 markers, 30 SNPs were selected to calculate allele frequencies. Pairwise F_{ST} values were all
249 significant (*Fig 2, Table S2*). The Red Sea had much higher F_{ST} values (ranging from 0.367 to
250 0.745) than any inter-Atlantic comparison (ranging from 0.029 to 0.135). However, all
251 comparisons within the Atlantic still showed significant F_{ST} values, the highest being between

252 the North Atlantic and Brazil, and the lowest between Brazil and Gulf of Mexico (*Fig 2, Table*
253 *S2*).

254

255 ***Nuclear loci***

256 Our nuclear data showed 4,988 variants of which 3,422 were biallelic SNPs and 151 were
257 multiallelic SNPs. A total of 346 SNPs remained after the same filtering process for the highest
258 quality SNPs was applied as for the mitochondrial genome. Nuclear markers showed lower F_{ST}
259 values between locations than the mitochondrial data, yet all P-values were still significant (*Fig*
260 *2, Table S2*). The Red Sea showed consistently higher F_{ST} values in comparison to inter-Atlantic
261 comparisons except for the North Atlantic to Gulf of Mexico comparison, which showed the
262 second highest mean F_{ST} value (*Fig 2, Table S2*). The highest value ($F_{ST} = 0.035$) was observed
263 between Gulf of Mexico and the Red Sea, whereas the lowest ($F_{ST} = 0.014$) was between the
264 North Atlantic and Brazil, which had the highest F_{ST} value within the Atlantic for the
265 mitochondrial data.

266

267 ***SNP validation***

268 SNPs called in the mitochondrial control region using the pool-seq protocol were compared with
269 those reported in Clarke et al. (2015). Of the 34 SNPs in their study 14 of them had a minor
270 allele count (MAC) of less than or equal to 3 and several were singletons. These SNPs are
271 removed from the pool-seq data due to MAC SNP filter of >3 to remove sequencing errors that
272 might be scored as rare alleles during high-throughput sequencing. Therefore, singletons or any
273 rare allele represented fewer than 3 times in a population will inherently be removed from pool-
274 seq data sets. Fortunately those rare alleles do not tend to overly impact F_{ST} values and should

275 not bias interpretations of population structure (Bird et al. 2011; Toonen et al. 2011). Three SNPs
276 were found in the Clarke study with a MAC of >3 that were not present in the pool-seq data;
277 however, the remaining 17 SNPs were all present in our data, plus one that was not found in the
278 Clarke study (*Fig S1*). Despite the loss of these rare alleles from the SNP validation set, pairwise
279 F_{ST} values estimated by both methods remained highly correlated (Mantel test, $r^2 = 0.96$, $p <$
280 0.05), and comparisons between the Red Sea and all three Atlantic populations showed the same
281 relative magnitude between both methods.

282 ***Cost Analysis***

283 The findings for cost analysis indicate that pool-seq reaches a threshold at approximately 300
284 individuals, after which this approach offers cheaper results than individual Sanger sequences.
285 Furthermore, the cost is only twice as expensive at just over 100 individuals (*Fig 3a*). The pool-
286 seq approach provides a far higher ratio of information for the cost, yielding greater population
287 resolution. This cost assessment does not include analytical time, labor, or effort associated with
288 pool-seq analyses such as access to computer resources and expertise with bioinformatic
289 pipelines. However these costs are likely to decrease in the near future as bioinformatic pipelines
290 are improved and become more widely available, for example as applications deployed via cloud
291 based platforms such as Galaxy (<https://usegalaxy.org/>) or CyVerse (<https://cyverse.org/>). It is
292 also important to note that the choice of pool-seq methodology has many caveats, which are
293 discussed in greater detail in the ‘considerations on pool-seq’ section of the discussion below.

294 **Discussion**

295 Elasmobranchs are being harvested at unsustainable levels in several commercial fishing
296 industries around the world. A fundamental step in successful management of any species is

297 resolving population boundaries so they can be managed on a genetic stock by stock basis. As
298 genetic sequencing technologies advance, there is greater opportunity to detect even small-scale
299 genetic differences between populations. When these differences amount to statically significant
300 allele frequencies at the population level, this indicates limited exchange among distinct stocks.

301

302 Here, we validate the utility of pool-seq using the same individuals as a previous study (Clarke et
303 al. 2015) and show that pool-seq recovers additional population structure relative to Sanger
304 sequencing of the mtDNA control region. Pool-seq was able to detect isolated populations
305 between the Gulf of Mexico, Western Atlantic, and along the Brazilian coast, where Clarke et al.
306 (2015) found no population structure. As expected, the Red Sea population was highly isolated
307 from Atlantic conspecifics using both approaches.

308

309 One advantage of this pool-seq approach is that we recover SNPs throughout the entire
310 mitochondrial genome along with thousands of additional nuclear loci that together provide
311 greater statistical power to detect finer scale population structure (Ryman & Palm 2006; Larsson
312 et al. 2009; Kurland et al. 2019). The pool-seq approach yielded significant genetic structure
313 among inter-Atlantic regions in both mtDNA and nuclear loci, whereas Sanger sequencing of the
314 mtCR lacked power to resolve significant differences among the same populations. The
315 congruence between the mitochondrial genome and nuclear loci reinforces the conclusion of
316 population structure among all regions sampled in this study.

317

318 In this case, pool-seq lived up to the promise of increased power to detect fine-scale structure,
319 but does it live up to the promise (Ferretti et al., 2013; Schlötterer et al., 2014) of being cost-

320 effective? Individual extraction costs remain fixed across both approaches and Sanger
321 sequencing generally has a flat rate per individual, including PCR primers and reagents, and
322 sequencing per individual per locus. In contrast, pool-seq has a flat sequencing cost determined
323 by the number of reads generated from the high-throughput sequencing platform, plus a small
324 additional cost per pool for the exact quantification of DNA for equimolar pooling and the
325 library preparation for high-throughput sequencing. Comparing costs at our institution between a
326 single Sanger sequencing marker and pool-seq on the Illumina MiSeq platform indicates pool-
327 seq becomes less expensive when sample size of the study rises above 300 individuals. Although
328 the cost per pool is essentially fixed, when higher numbers of individuals are included per pool,
329 the price per individual analyzed is further reduced (*Fig 3b*). Our comparison here is limited to
330 12 pools due to the maximum number of reads per lane produced on the MiSeq platform.
331 Therefore, analyzing more than 12 pools would require additional sequencing runs and result in a
332 step increase in the cost per individual/pool, although this would differ among other Illumina
333 machines (such as the HiSeq, NextSeq or NovaSeq) or other high-throughput sequencing
334 platforms (such as the PacBio Sequel II). Larger numbers of pools could be run on some of these
335 machines, but with differing individual read lengths and sequencing depths, which also bring
336 other trade-offs. Likewise, samples can also be run with individual barcodes, therefore gaining
337 the individual information lost by pooling specimens, but with increased initial setup and
338 sequencing costs. There are so many options by which to apply these methods that we cannot
339 possibly consider them all here, and the availability, cost, and trade-offs associated with each
340 should be ideally considered by individuals when designing high-throughput sequencing
341 projects. In our case, we considered only the options currently available to us through our
342 campus sequencing core, and all these pool-seq price comparisons are to a single Sanger-

343 sequenced marker. Thus, when considering the information acquired from pool-seq compared to
344 the cost from traditional single mitochondrial marker the price per individual advantage is
345 massively amplified.

346

347 *Considerations with pool-seq*

348 As with any sequencing technique, there are still several factors to consider before deciding if
349 pool-seq is appropriate for a particular study. Multiple reviews have been published on high-
350 throughput and pool-seq approaches demonstrating pros, cons, and considerations with these
351 methods, which are beyond the scope of this study. Interested readers should consult Perez-
352 Enciso & Ferretti (2010), Futschik & Schlötterer (2010), Kofler et al. (2012), Ferretti et al.
353 (2013), Schlötterer et al., 2014, Andrews & Luikart (2014), Andrews et al. (2016), and Kurland
354 et al. (2019).

355

356 Pooling assumes individuals are from the interbreeding individuals within a single population of
357 the same species. Therefore, care needs to be taken to avoid cryptic species, combining multiple
358 populations (Wahlund effect), or other unintentional bias when selecting individuals to pool
359 (Garnier-Géré & Chikhi 2013). For wide ranging pelagic species such as the blue shark or
360 oceanic whitetip it seems reasonable to pool individuals from a larger area than it would be for
361 small benthic species such as horn sharks, wobbegongs, or most rays. Population structure may
362 be obscured if the geographic range per pool is too large or if there is complex population
363 structure (*sensu* Bowen et al. 2005), because individuals from multiple sub-populations will be
364 mixed into a single pool from which allele frequencies are calculated. Certainly pool-seq is not
365 appropriate in all cases. It is a cost-saving approach for analyses based on allele frequencies

366 only, because individual information is lost by pooling, including haplotypes/genotypes and
367 linkage disequilibrium information. Also, pooling makes it difficult to distinguish between low
368 frequency alleles in the population and sequencing error. Therefore, careful filtering must be
369 applied to ensure only valid SNPs are analyzed instead of analyzing sequencing noise (Anand et
370 al., 2016; Schlötterer et al., 2014). Finally, the estimation of F_{ST} from pooled data remains a
371 subject of some debate, and new approaches and bias corrections are being actively developed
372 (Kofler et al. 2011; Hivert et al. 2018). To account for this uncertainty, we include analyses
373 based on both the original PoPoolation2 (Kofler et al., 2011) package and the newer poolfstat
374 (Hivert et al., 2018) that explicitly considers potential biases associated with varying pool sizes.
375 The two approaches yield slightly different F_{ST} values (see *Table S2*), however a comparison of
376 the two F_{ST} matrices shows strong correlation (Mantel $r=0.991$ for mitochondrial and $r=0.978$ for
377 nuclear data, $p < 0.05$). Therefore, only those F_{ST} values calculated by PoPoolation2 are reported
378 in the main text for ease of presentation.

379

380 Though pool-seq has been shown to be an affordable and reliable tool for population genomics
381 (Futschik & Schlötterer, 2010; Gautier et al., 2013; Rellstab et al. 2013; Konczal et al. 2014;
382 Schlötterer et al. 2014; Kurland et al. 2019), projects with larger budgets could allocate funds for
383 any of a variety of other genomic sequencing techniques such as individual RADseq libraries
384 (Hohenlohe et al. 2010), GBS (Narum et al. 2013), SNP arrays (Qi et al. 2017), bait capture
385 (Feutry et al. 2020), or low coverage genomewide sequencing (Therkildsen & Palumbi 2017).
386 These approaches allow for individual genotyping to examine questions that require individual-
387 level information and could provide a deeper assessment of populations. However it is also
388 important to consider not all labs can afford to generate genomic level data, especially in

389 developing countries, and having a cost-effective alternative to single marker studies will
390 continue to be invaluable to many.

391

392 **Conclusions**

393 The finding of population structure on the scale of North Atlantic/Gulf of Mexico/Brazil is
394 nearly unprecedented for a pelagic shark. Population structure in globally distributed sharks is
395 typically detected on a scale of ocean basins (Atlantic versus Indo-Pacific, Castro et al. 2007;
396 Graves & McDowell, 2015) and a few pelagic fishes have no population structure on a global
397 scale (e.g. Basking shark, *Cetorhinus maximus*, Hoelzel et al. 2006; Blue shark *Prionace glauca*,
398 Veríssimo et al. 2017; Wahoo, *Acanthocybium solandri*, Theisen et al. 2008). The resolution of
399 isolated populations on the scale of North Atlantic Ocean is more typical of coastal species than
400 pelagic species. The silky shark seems to be a pelagic species with a somewhat coastal
401 population structure. This has strong implications for international management because smaller
402 stocks imply smaller populations which are more readily depleted. At a minimum, these data
403 require rethinking a single population management approach for the Atlantic, and this pattern
404 needs to be investigated for this species across the Indo-Pacific as well.

405

406 Overall this study demonstrates pool-seq is a powerful and cost-effective tool for analyzing large
407 portions of the genome which the methods traditionally used for elasmobranchs could not
408 supply. Sharks and rays are an imperiled group of species that could benefit from advanced
409 genomic studies to outline appropriate management units. Finally, although the technology is
410 becoming cheaper and easier to apply, it is a common pitfall to assume everyone in the field can
411 afford, or must use, these approaches to produce defensible science. Bowen et al. (2014)
412 advocate judicious rather than wholesale application of genomic approaches as the most robust

413 course of study, particularly when considering the global inequities in available research budgets.
414 Sanger sequencing is still more cost effective for small numbers of individuals, but as the
415 number of individuals included in a study rise, the cost per individual reaches the point where
416 high throughput sequencing studies can be cheaper than sequencing a single mitochondrial
417 marker from each individual. We provide an example of just such a case here, and highlight the
418 potential advantage of cost savings together with increased power for resolution of fine scale
419 population structure. Though there is still additional cost of using cluster computer servers and
420 bioinformatics programs, these cost are dropping as technology advances. When study organism
421 and sampling strategies are assessed and implemented into the study design, pool-seq has great
422 promise for augmenting the scientific foundations for management of marine resources.

423

424 **Acknowledgements**

425 This study was made possible by the generous donation of specimens by Christopher R. Clarke,
426 Mahmood Shivji, Stephen A. Karl, J.D. Filmalter, and Julia Spaet. We thank members of the
427 ToBo Lab for sharing expertise, advice and discussions that contributed to this manuscript.
428 Special thanks to Darren Lerner, Kim Holland, Carl Meyer, S. Gulak, D. Bethe, D. McCauley, C.
429 Wilson, Guy Harvey Ocean Foundation, and Save Our Seas Foundation. This paper is funded in
430 part by a cooperative agreement from the National Oceanic and Atmospheric Administration,
431 Project R/SS-19PD, which is sponsored by the University of Hawai'i Sea Grant College Program
432 under Institutional Grant No. NA14OAR4170071 (B.W.B) from NOAA Office of Sea Grant,
433 Department of Commerce. The views expressed herein are those of the authors and do not
434 necessarily reflect the views of NOAA or any of its subagencies. This is contribution #1821 from
435 the Hawaii Institute of Marine Biology, contribution #XXXX from the Hawaii Sea Grant

436 Program, and contribution #11128 from the School of Ocean and Earth Science and Technology
437 at the University of Hawaii.

438 **Author Contributions:**

439 Derek W. Kraft – Designed research, performed research, analyzed data, wrote paper, provided
440 funding for research.

441 Emily Conklin – Created bioinformatics pipeline for data analysis and assisted in data analysis

442 Evan Barba – Created bioinformatics pipeline for data analysis and assisted in data analysis

443 Melanie Hutchinson – Helped obtain samples and provided biological insight

444 Robert J. Toonen – Contributed funding, contributed to research design, and contributed to data
445 analysis and edited paper

446 Zac H. Forsman – Contributed to research design and data analysis

447 Brian W. Bowen – Contributed funding, contributed to research design, and edited paper

448

449 **References**

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Figure 1

Sample locations of *Carcharhinus falciformis* followed by sample size

Abbreviations: GM = Gulf of Mexico, NA = North Atlantic, BR = Brazil, RS = Red Sea.

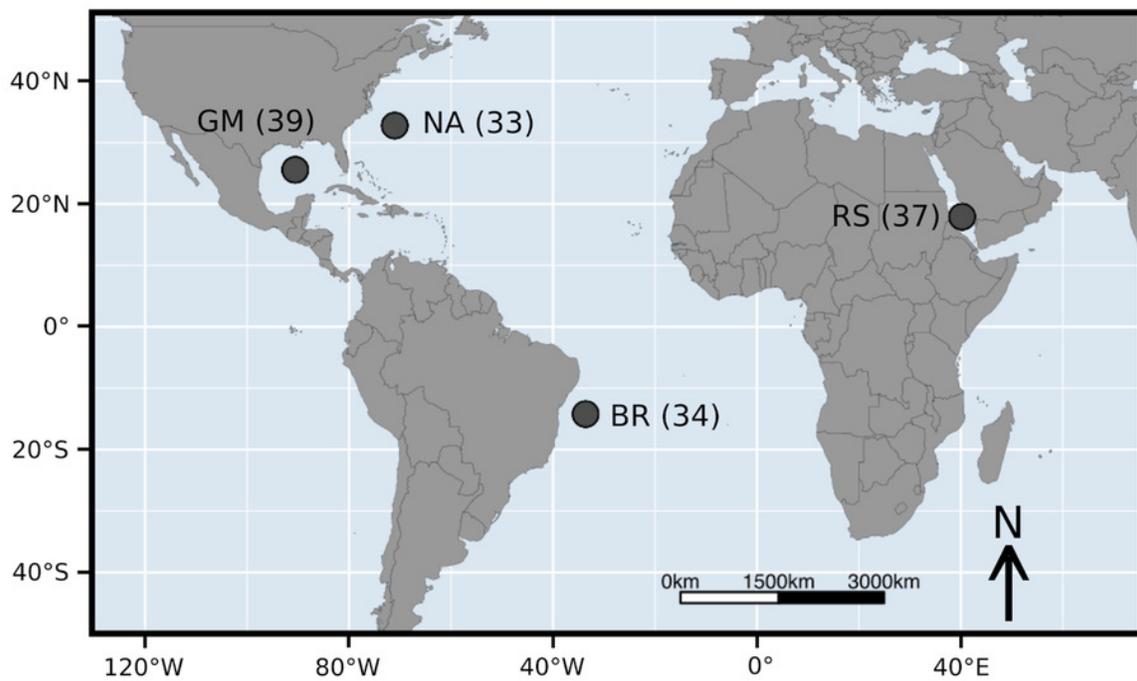


Figure 2

F_{st} heat map for mitochondrial and nuclear data compared to Clarke et al. Φ_{st} and P-values

Figure 2. (A) Pairwise F_{ST} values generated by Pool-seq methods. Cool colors (top left) are F_{ST} values calculated from nuclear genome loci, warm colors (bottom right) are F_{ST} values from loci across the entire mitochondrial genome. All pairwise differences are significant ($p < 0.001$). **(B)** Φ_{iST} results from Clarke et. Al (2015) on the lower right triangle and P-values on the upper right triangle. Significant P-values and corresponding Φ_{iST} values in bold. Regional abbreviation are as follows; GM = Gulf of Mexico, BR = Brazil, NA = North Atlantic, RS = Red sea.

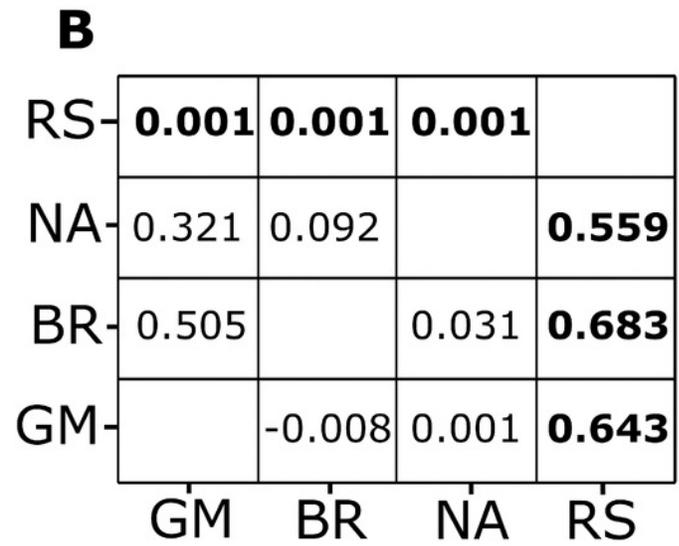
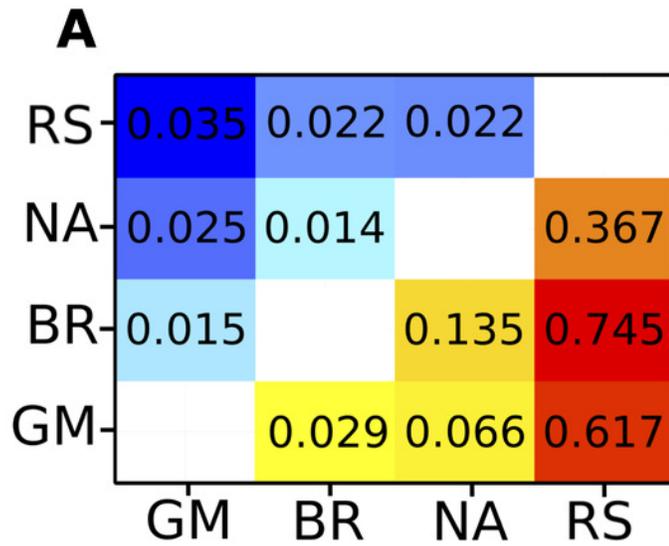


Figure 3

Cost comparisons between sequencing projects using a single Sanger marker to projects using Pool-seq with varying numbers of pools.

(A) Sequencing costs comparing number of individuals to total cost between Sanger at our facility and three Pool-seq projects at our facility containing 4, 8, and 12 pools respectively, where pool sizes change with number of individuals. **(B)** Sequencing cost per individual with fixed pools across different number of Pools.

