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1 **Performance and precision of double digestion RAD (ddRAD) genotyping in large**
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35 **Abstract**

36 The development of Genotyping-By-Sequencing (GBS) technologies enables cost-effective
37 analysis of large numbers of Single Nucleotide Polymorphisms (SNPs), especially in ‘non-
38 model’ species. Nevertheless, as such technologies enter a mature phase, biases and errors
39 inherent to GBS are becoming evident. Here, we evaluated the performance of double digest
40 Restriction enzyme Associated DNA (ddRAD) sequencing in SNP genotyping studies
41 including high number of samples. Datasets of sequence data were generated from three marine
42 teleost species (>5,500 samples, >2.5x10¹² bases in total), using a standardized protocol. A
43 common bioinformatics pipeline based on STACKS was established, with and without the use
44 of a reference genome. We performed analyses throughout the production and analysis of
45 ddRAD data in order to explore (i) the loss of information due to heterogeneous raw read
46 number across samples; (ii) the discrepancy between expected and observed tag length and

47 coverage; (iii) the performances of reference based vs. *de novo* approaches; (iv) the sources of
48 potential genotyping errors of the library preparation/bioinformatics protocol, by comparing
49 technical replicates. Our results showed use of a reference genome and *a posteriori* genotype
50 correction improved genotyping precision. Individual read coverage was a key variable for
51 reproducibility; variance in sequencing depth between loci in the same individual was also
52 identified as an important factor and found to correlate to tag length. A comparison of
53 downstream analysis carried out with ddRAD vs single SNP allele specific assay genotypes
54 provided information about the levels of genotyping imprecision that can have a significant
55 impact on allele frequency estimations and population assignment. The results and insights
56 presented here will help to select and improve approaches to the analysis of large datasets based
57 on RAD-like methodologies.

58 **Introduction**

59 The options for studying the genomic constitution of individuals and populations are increasing
60 rapidly thanks to the development of powerful and accurate sequencing technologies that
61 provide higher throughput at decreasing costs (Liu et al. 2012). Meanwhile, efficient reduced
62 representation methods have been proposed to provide high sequence coverage for selected
63 genomic regions, collectively named as Genotyping-By-Sequencing (GBS) technologies
64 (Narum et al. 2013). One of these GBS methods, Restriction-site Associated DNA sequencing
65 (RAD-seq) (Baird et al. 2008) has become particularly popular as it allows the cost-effective
66 analysis of thousands of markers for tens/hundreds of individuals in a single sequencing lane.
67 The original RAD protocol has also been modified to optimize throughput and ease of use,
68 generating several alternative RAD-like methods (*e.g.* Peterson et al. 2012; Wang et al. 2012;
69 and the review by Andrews et al. 2016).

70 As GBS technologies enter a more mature phase, biases and errors inherent to such methods
71 are becoming apparent (Arnold et al. 2013) and comparative analysis of the most popular RAD-
72 like protocols have addressed some of these subjects (Puritz et al. 2014). Two recent studies
73 (DaCosta e Sorenson 2014; Mastretta-Yanes et al. 2015) focused specifically on genotyping
74 issues relating to double digest Restriction enzyme Associated DNA (ddRAD) (Peterson et al.
75 2012). ddRAD is one of the most recently developed RAD variants, known for its relative
76 flexibility and ease of use. In addition to the sources of error that also affect other methodologies,
77 the authors recorded ddRAD-specific issues such as the recovery of restriction fragments
78 shorter than expected, amplification bias toward GC-rich fragments, non-specific cutting by
79 restriction enzymes, newly formed restriction enzyme sites and drop of fragment number due
80 to loss of restriction sites.

81 Beyond laboratory-based assessments of variation in ddRAD performance, there is a need to
82 better understand the risk of errors associated with the production and use of ddRAD data,
83 which is becoming increasingly relied upon for population genetic inference. Unawareness of
84 the presence of biased markers can indeed lead to artificial excess of homozygotes (Taberlet et
85 al. 1996), false departure from Hardy–Weinberg equilibrium (Xu et al. 2002), overestimation
86 of inbreeding (Gomes et al. 1999) and unreliable inferences about population structure that have
87 the potential to distort research conclusions. As a consequence, natural resource management
88 and policy can be seriously affected. In this study, we seek to expand the experimental
89 evaluation of ddRAD by focusing on the performance of common bioinformatics approaches
90 as applied to multiple, comparable, large ddRAD datasets of marine fish species. A technical
91 evaluation focused on marine fish data is interesting due to some biological characteristics of
92 this taxon, such as relatively high SNP frequency, that can further affect genotyping accuracy.
93 The species analyzed in this study are the European sea bass (*Dicentrarchus labrax*), the
94 gilthead sea bream (*Sparus aurata*) and the turbot (*Scophthalmus maximus*).

95 Available genomic resources are increasing for three species studied. Sea bass (Tine et al. 2014)
96 and turbot (Figueras et al. 2016) genomes have already been published and a draft sea bream
97 genome will soon be published (L. Bargelloni, personal communication) and was made
98 available for this work. The three differ in the quality of their assembly, as indicated by the
99 contig length (i.e. their respective N50 values, which is defined as the length N for which 50%
100 of all bases in the sequences are in a sequence of length $L < N$). However, they share similar
101 genome size and can thus provide comparable results (Table 1). The use of species with
102 different levels of genome sequence development permits assessing effects of the reference
103 genome quality on approaches that use genomes to improve the performance of clustering

104 methods for RAD data (e.g. reference based analysis in STACKS).

105 In this study, we set out to examine how variation in ddRAD sequence datasets and the
106 application and quality of available reference genome sequences affect the consistency and
107 accuracy of resulting data, generated through commonly used analytical approaches. The
108 laboratory and bioinformatic pipeline used to generate the ddRAD datasets followed standard
109 published methods (see below) and has been summarized in a flowchart (Figure 1). The
110 performance of the ddRAD pipeline was evaluated at different stages in order to investigate the
111 causes and effects of variation in individual sample coverage, RAD-tag sequence length and
112 application and quality of reference genomes on the eventual accuracy and error rates of
113 individual genotyping. We specifically addressed the following questions:

- 114 (i) *Evaluation of sample representation within multiplexed libraries.* What is the
115 typical variation in terms of number of raw reads per sample when multiple
116 individuals (144 in our case) are multiplexed in a single sequencing lane?
- 117 (ii) *Tag length and coverage.* Is there any difference between the expected and observed
118 length of analyzed tags? Does any relationship exist between tag length and depth
119 of coverage?
- 120 (i) *De novo and reference-based genotyping using STACKS.* What is the effect of
121 different clustering approaches (e.g. *de novo* vs reference-based, *a posteriori*
122 genotyping correction) on the number of markers identified?
- 123 (ii) *Genotyping precision and error rates.* What are the effects of the variables described
124 above on the number of mismatches between technical replicates?

125 Based on these insights we suggest approaches which can help to mitigate the identified risks
126 of error in ddRAD analysis. Finally, the potential effect of genotyping imprecision on

127 downstream analysis was evaluated using comparative data between ddRAD and single SNP
128 allele specific genotyping, focusing on how genotyping errors could affect allele frequency and
129 population assignment.

130 **Material and Methods**

131 *Samples and library preparation*

132 Specimens of European sea bass, gilthead sea bream and turbot were collected in the context of
133 the European Union's FP7 funded project 'AQUATRACE' (KBBE 311920). The entire sample
134 set included more than 5,581 specimens (2,128 European sea bass, 2,156 gilthead sea bream
135 and 1,297 turbot) from the species' distribution range, some of which were collected
136 specifically for the project (years 2013-2014, from now on referred to as "fresh" samples), while
137 others had been collected earlier ("archived" samples) (Supplementary Material Table). For
138 fresh samples, fin clips were preserved separately in 95% ethanol at 4°C until genomic DNA
139 (gDNA) extraction. Samples were extracted either with Invisorb® DNA tissue HTS 96 kit
140 (Strattec biomedical) or with a standard NaCl isopropanol precipitation protocol (Cruz et al.
141 2016). Extracted DNA samples were then classified as "high", "mid" or "low" quality
142 according to the level of degradation assessed with agarose gel electrophoresis (see
143 Supplementary material).

144 The same ddRAD protocol, with minor modifications, was used for the three species. The
145 library preparation followed the original guidelines of Peterson et al. (2012), with some
146 modifications that facilitate the screening of large number of individuals (see Supplementary
147 Material for details), and was carried out in three different laboratories within the AquaTrace
148 consortium, each focusing on a single species: the sea bass at the Laboratory of Biodiversity
149 and Evolutionary Genomics, University of Leuven, sea bream at the Department of Compared

150 Biomedicine and Food Science, University of Padova and turbot at the Departamento de
151 Zoología, Genética y Antropología Física, Universidade de Santiago de Compostela. To
152 promote a common standardized approach, staff from the three laboratories completed a hands-
153 on training course in library preparation at the Institute of Aquaculture, Stirling, where the
154 modified ddRAD protocol originated. Multiple ddRAD libraries were prepared for each species
155 (sea bream n=14; sea bass n=14; turbot n=9). Each library comprised 144 samples, and in all
156 the libraries the same three or four control samples for each species were included, to enable
157 cross-library comparisons and mismatch rates between replicates to be assessed. In particular,
158 four sea bream specimens (SAC3, SAC4, SAC5 and SAC6 from Sardinia, Italy); three sea bass
159 specimens (DLTY40, from the Central Mediterranean Sea; DLM44, from the Atlantic and
160 DLFF1, from a European broodstock); and four turbot specimens (SMFF1, SMFF2 and SMFF3
161 from a Spanish broodstock; SMNS32 from North Sea's wild population) were used.

162 *Sequence data analysis – standard pipeline*

163 The following approach to sequence data analysis was used for all datasets as the basis for
164 subsequent comparative analysis. Raw data were filtered to retain only high quality reads, using
165 STACKS 1.28 (J. Catchen et al. 2013; J. M. Catchen et al. 2011) *process_radtags* program,
166 which allows simultaneous quality filtering and sample demultiplexing. After barcode removal
167 (5-7 bases), the sequences were 3' end-trimmed to a standard 90 nucleotides length. Each read
168 was then analyzed to assess sequence quality. Briefly, a 3-base sliding window (STACKS'
169 option -w) was used to parse each read and where the average phred score of three consecutive
170 bases was lower than 20 (STACKS' option -s) the entire read was discarded.

171 STACKS was also used for clustering reads and for SNP discovery, following standard *de novo*
172 and reference based pipelines, well described in the program website

173 (<http://catchenlab.life.illinois.edu/stacks/>). In our case parameter $-m$ (minimum number of
174 reads to call a stacks) was set to four and $-M$ (maximum number of mismatches between reads
175 to be considered as part of the same cluster) was set to five, according to the suggestion of
176 Mastretta-Yanes (2015), and considering the longer reads of our study (due to concatenation).
177 For the *de novo* approach, reads from primer P1 were concatenated with the reverse
178 complement sequence of reads from primer P2, obtaining 180 bp *pseudo-contigs*. This approach
179 was used to create longer sequence tags which reduces the risk of over-merging (i.e. clustering
180 together tags coming from different genomic regions) by keeping the information about relative
181 proximity of Read 1 and Read 2. As an added benefit, this approach allowed to be fully aware
182 of linkage issues. Since reference based approach require reads to be mapped against a reference,
183 we used the software package BOWTIE (Langmead et al. 2009), considering read pairing in the
184 alignment process. We kept only read pairs that matched a single genomic position.
185 When building the RAD-tag catalog a maximum number of five mismatches between tags was
186 set. For the reference-based approach, clustering was based on mapping position. Within a stack
187 containing variant reads (i.e. potential SNPs), the following call thresholds were used: rare
188 variant frequency (rvf) <0.01 = homozygote; $0.01 < rvf < 0.1$ = 'genotype unknown'; $rvf > 0.1$ =
189 heterozygote called. *rxstacks*, STACKS' component that corrects genotypes on the basis of
190 population information, was also implemented for comparison. Finally, we used the algorithm
191 implemented in STACKS' *populations* step to retain only individual loci represented with at
192 least 10 reads per individual sample and genotyped in at least 80% of the samples analyzed.
193 This is an important step when the genotypes of multiple individuals need to be compared, as
194 only shared loci provide useful information for genetic analysis.

195 *Analysis of the pipeline*

196 Here, we describe the methods used to assess the pipeline based on the four issues described in
197 the Introduction (Figure 1).

198 (i) *Evaluation of sample representation within multiplexed libraries*

199 Considering the number of samples multiplexed and the average output of the sequencing
200 platform/chemistry (180 M reads), approximately 1.3 M reads per sample are theoretically
201 expected. However, even if initial DNA quantification is accurate and input DNA is equal
202 among samples, subsequent library preparation steps may alter individual representation within
203 the library resulting in variability in inter-sample sequencing effort. To investigate sample read
204 homogeneity in libraries with up to 144 pooled individuals, we first established a threshold
205 number of reads per sample against which to filter individual sample data. A threshold of 150
206 k reads was chosen as a minimum to accept an individual sample for downstream data
207 processing, based on an expected number of 7,000 stacks per sample (estimated from *in-silico*
208 analysis) and an average coverage of 20x. This threshold was used in the analysis of the
209 sequencing output for all available ddRAD data including more than 5,000 samples.

210 To identify the factors correlated with fewer reads, we tested the correlation between number
211 of reads (above or below the threshold) and variables such as “DNA quality”, whether a sample
212 was “fresh” or “archived”, “individual sample collector” (i.e. the project partner that collected
213 the sample), and “index barcode” (different length/sequence barcodes could perform differently
214 in the amplification or sequencing by synthesis steps), testing the effect of each variable under
215 a Generalized Linear Model (GLM), as implemented in R 3.2.3 library function Rcmdr (Team
216 2013; Fox 2005). Chi-squared tests were applied to check association between tested variables.

217 For the analysis described further on, only replicate samples with sufficient read numbers were
218 used.

219 (ii) *Tag length and coverage*

220 To understand whether the length of the RAD-tags ('tag length') observed corresponded to the
221 expected length (i.e. the 'insert length' from size selection minus adapter length) and to
222 investigate association between tag length and coverage, we extracted fragment length and
223 DNA sequences of ddRAD-tags from BOWTIE alignment results. Data on coverage depth was
224 extracted for each single locus of each sample, separately. To allow comparison between
225 samples with different average coverage, standardized coverage depth was obtained by dividing
226 locus specific values by the average coverage across all loci for each sample. Similarly, when
227 comparing the distribution of the number of tags with different lengths, 10 bp bins were used
228 and the relative number of tags was calculated dividing the number of tags of a certain length
229 bin by the average number of tags across all the bins. A Wilcoxon signed-rank test, as
230 implemented in R 3.2.3 library Rcmdr (Team 2013; Fox 2005), was used to test for differences
231 between distributions from the three datasets.

232 (iii) *De novo and reference-based genotyping using STACKS*

233 In order to understand how the alignment to a reference genome influences SNP genotyping,
234 we obtained individual genotypes using both *de novo* and reference-based analysis in STACKS.
235 Since we expected *de novo* approach to detect also tags that are not contained in the reference
236 genome, we wanted to evaluate the amount of *de novo* tags that could be found in the genome.
237 In order to do this, RAD-tags resulting from *de novo* analysis (180 bp long) were subsequently
238 split in two (in order to reconstitute the original 90 bp tags) and mapped against the reference
239 genome using BOWTIE, with the same parameters used while aligning reads for reference based
240 analysis. Under both *de novo* and reference-based analysis, results were compared with and
241 without the final step in *rxstacks*. Statistical differences between approaches were tested with

242 chi-squared tests.

243 (iv) *Genotyping precision and error rates*

244 To investigate the level of reproducibility across different bioinformatic approaches we
245 examined the level of consistency among scored SNP genotypes within the sets of nine to 15
246 replicated samples for each species. The most frequent genotypes were considered as the
247 “correct” ones, and mismatches were counted for each locus in each sample to estimate
248 genotyping error.

249 When comparing results from different approaches, statistical significance was tested using
250 either on-line applications (e.g. Kruskal-Wallis: <http://vassarstats.net>) or the Rcmdr library for
251 R 3.2.3 (Team 2013; Fox 2005). A first global analysis was carried out to assess the effect of
252 several parameters (“coverage”, “genome reference” mapping, “*rxstacks* correction”,
253 percentage of high-quality reads) on mismatch rate across the entire dataset. Individual
254 mismatch rates were classified either as a binary outcome (0 for values lower than the overall
255 median mismatch rate, 1 for those equal or greater), or grouped into quartiles for a finer
256 evaluation of the effects of different explanatory factors. In both cases, either a Generalized
257 Linear Model (used with binary outcome) or Ordinal Linear Regression (used with samples
258 grouped into quartiles) were used to detect the most influential variables. The same statistical
259 approach was then implemented, within each dataset, across single specimens, to look more
260 into detail at individual-specific features that could affect genotyping quality and to avoid
261 dataset-specific biases and errors. This additional analysis was possible thanks to the large
262 number of replicates available for each species and the standardization of library preparation
263 technique and bioinformatics protocols. Lastly, mismatch rates were analyzed across loci, to
264 check the expectation that, within each “species+strategy” dataset (e.g. sea bream+*de novo* or

265 turbot+reference based) loci with lower average coverage also showed higher mismatch rates.

266 *Assessing the impact of genotyping accuracy*

267 The impact of genotyping imprecisions on downstream applications varies depending on the
268 type of analysis carried out. Since the principal applications of the project data were the analysis
269 of genetic structure, based on allele frequency, and the development of traceability tools, based
270 on population assignment, we evaluated the impact of variation in genotype scoring on these
271 applications. To do this, we used a reduced set of highly informative markers (14 for sea bass,
272 15 for sea bream and 18 for turbot) genotyped with both ddRAD and with a single SNP allele-
273 specific assay (KASP). Using these approaches we genotyped 22, 25 and 22 samples of sea
274 bass, sea bream and turbot, respectively. Comparison of the two genotype datasets was
275 conducted at the following three levels: a) *Genotype data*: a simple analysis of genotype
276 mismatch between data from the two approaches analysed in the same individual fish, with missing
277 data differentiated from observed differences in genotype; b) *Allele frequency data*: the impact of
278 individual genotyping mismatches on allele frequencies was assessed by testing for statistical
279 significance (Student's T-tests) between allele frequencies across all loci, with genotype
280 differences not differentiated from missing data in their effect on allele frequencies; c) *Individual*
281 *assignment data*: assignment was conducted using GeneClass2 software (Piry et al. 2000).
282 Individual assignment scores (%) output from GeneClass2 were used to assess differences in
283 assignment of individual genotypes produced using the two methods and significance was assessed
284 using Student's T-tests. Reference data for population assignment consisted of a larger set of more
285 than 900 wild and farmed samples for the three species genotyped with ddRAD.

286

287 **Results**

288 The first part of the study addressed the loss of analytical power in terms of number of samples
289 filtered due to unequal representation of individuals within libraries; it was based on a data set
290 of more than 5,581 samples, in which the replicate individuals were included.

291 (i) *Evaluation of sample representation within multiplexed libraries*

292 As indicated by high values of standard deviation (in particular for turbot), variation in the
293 number of raw reads among individuals within species was very high. In fact, 129 samples (71
294 sea bass, 16 sea bream and 42 turbot) were represented by less than 1,000 reads and three
295 samples (all in turbot dataset) had more than 5,000,000 reads. Using the threshold of 150,000
296 raw reads, 6.8% of sea bass samples, 8.1% of sea bream samples and 16.0% of turbot samples
297 were discarded. After quality filter was applied, an average of $74.5\% \pm 10.8\%$ reads remained
298 available for further analysis. After filtering, the average number of high quality reads was
299 similar across species, $687,426 \pm 447,701$ in European sea bass, $614,099 \pm 406,018$ in gilthead
300 sea bream and $610,703 \pm 707,152$ in turbot. Regression analysis indicated that better quality
301 DNA resulted in higher number of high quality reads ($t = -11.4$ $p < 0.001$); similarly, “fresh”
302 samples had a higher amount of high quality reads than “archived samples” ($t = -3.1$ $p < 0.005$).
303 “DNA quality” of individual samples was neither significantly associated with species ($X^2 = 4.6$
304 $p > 0.25$), nor with fresh/archived condition ($X^2 = 3.1$ $p > 0.25$). The DNA of 129 samples showing
305 less than 1,000 reads were all of good quality, which means that inaccurate quantification or
306 pipetting errors are probably what caused this strong under-representation.

307 After filtering and quality checking, the final number of replicated samples available for
308 downstream analysis was 111: 43 sea bream samples (11 replicates for SAC3, 11 for SAC4, 10
309 for SAC5 and 11 for SAC6) genotyped across 11 independent libraries, 34 sea bass samples (5
310 replicates for DLCTY_40, 14 for DLT_1 and 15 for DLM_44) genotyped across 15 libraries

311 and 34 turbot samples (9 replicates for SMFF1, 8 for SMFF2, 9 for SMFF3 and 8 for SMNS32)
312 genotyped across 9 libraries.

313 (ii) *Tag length and coverage*

314 On average across species, 78.4% of the reads were successfully mapped on the reference
315 genomes and mapping rates ranged from 71.3% uniquely mapped reads in sea bream to 85.4%
316 in sea bass.

317 Average tag length across datasets was 288.9 ± 110.5 bp. Most of the tags (79.5%) were 100-
318 380 bp. In addition, substantial fractions (21.1% sea bream, 24.5% sea bass, 15.9% turbot) of
319 analyzed RAD-tags were shorter than 190 bp (the minimum size expected according to the
320 library construction protocol) (Figure 2). Paired-tests between datasets suggested that size
321 distribution was not significantly different across species (Wilcoxon signed-rank test, bream-
322 bass $p=0.803$, bream-turbot $p=0.865$, bass-turbot $p=0.984$).

323 Although average coverage depth per locus differed among datasets for the three species (157
324 ± 94 for sea bass, 248 ± 126 for sea bream, 700 ± 544 for turbot), relative coverage was evenly
325 distributed (Wilcoxon signed-rank test, bream-bass $p=0.697$, bream-turbot $p=0.865$, bass-turbot
326 $p=0.689$) with respect to RAD-tag length (Figure 3). Significant ($p<0.01$) positive linear
327 correlations between length and coverage were also found for fragments in the range from 100
328 to 250 bp (Spearman $\rho=0.903$ in sea bream, 0.957 in sea bass and 0.918 in turbot). Fragments
329 longer than 250 bp showed significant ($p<0.01$) negative linear correlation between length and
330 coverage (Spearman $\rho=-0.969$ in sea bream; -0.968 in sea bass, -0.952 in turbot). No
331 significant correlation between GC content of fragments and coverage depth was observed.

332 (iii) *De novo and reference-based genotyping using STACKS*

333 The number of independent RAD-tags identified varied depending on the approach. In all cases

334 the number of tags found by the reference genome-based approach was much lower than that
335 found with the *de novo* approach (up to 5.5 times, in turbot dataset) (Table 2). However, when
336 a filter was applied to retain only tags shared by at least 80% of samples analyzed, higher
337 proportion was retained for reference-based analysis (on average 44.9%±19.7%) than *de novo*
338 analysis (on average 9.1%±6.0%). This made that in most cases the final number of retained
339 tags was higher using the reference-based approach. Similarly, a higher number of SNPs was
340 observed in the reference-based approach after filtering. The application of the genotype
341 correction implemented in *rxstacks* reduced the number of tags by different extents: a minimum
342 of 63% of total tags were retained in the turbot reference-based analysis and a maximum of
343 99.6% in the sea bass *de novo* analysis. The proportion of SNPs retained was comparable,
344 ranging from 56.9% to 99.8% in turbot (reference-based) and sea bass (*de novo*), respectively.
345 Mapping tags from *de novo* analysis against the reference genomes produced 11,121 matches
346 for sea bass (28.3% of *de novo* RAD tags); 11,650 for sea bream (23.0% of *de novo* RAD tags)
347 and 7,889 for turbot (6.8% of *de novo* RAD tags). These figures are in agreement with the
348 relative length of the genomes utilized (Table 1), while the lower than expected difference
349 between sea bass and sea bream results can be explained by the lower quality of the bream
350 assembly, as indicated by the N50 value.

351 (iv) *Genotyping precision and error rates*

352 Our analysis suggested that “*rxstacks* correction” and “coverage” significantly affected the
353 level of accuracy in the comparison of different approaches, regardless the species. In particular,
354 lower mismatch rate were recorded when *rxstacks* was implemented and when coverage depth
355 per sample was higher. However, variation in mismatch rates were found between different
356 species datasets (Table 3); they were apparently linked with differences in species-specific

357 coverage, which varied significantly both for *de novo* RAD-tags (Kruskall-Wallis test, $H=15.27$
358 $p<0.001$) and reference-based ones (Kruskall-Wallis test, $H=30.74$ $p<0.0001$). To overcome
359 biases linked to species-specific differences, more specific tests were carried out within single
360 datasets. In fact, additional factors were found to be significantly affecting mismatch rate. In
361 addition to “*rxstacks* correction”, also “library”, “reference-mapping” and “sample” (only in
362 the turbot database) showed significant correlations. At species level, “Coverage” showed a
363 significant correlation in two out of three datasets (sea bream ($p<0.05$) and turbot ($p<0.001$)).
364 Nevertheless, across loci (i.e. within “single species+strategy” dataset) no significant
365 correlation between mismatch and coverage was found.

366 *Impact of genotyping accuracy on population assignment*

367 The percentage of samples with at least one different genotype observed in sea bass, sea bream
368 and turbot was 31.5% (seven samples), 52% (13 samples) and 36% (eight samples), respectively,
369 reflecting a total level of genotyping variation of 3.7% in sea bass (nine allelic differences), 4.8%
370 in sea bream (eighteen allelic differences) and 3.0% in turbot (12 allelic differences). Resulting
371 allele frequencies differed significantly at one locus in sea bream, that displayed the largest single
372 allele frequency difference between the two genotype datasets (11.5%). A similar single locus
373 deviation was observed in sea bass, despite the overall difference being non-significant. The effect
374 of genotyping mismatch on individual assignment was lower; only for turbot, was one individual
375 assigned to different populations of origin with the two genotype datasets. On closer inspection,
376 the two genotypes for this sample differed at three alleles observed at two loci. The two genotypes
377 at first locus were alternate homozygotes, whereas the other discrepancy was between
378 heterozygous and homozygous genotypes at another locus. Further analysis of the sample based
379 on population exclusion testing revealed that neither population of origin (wild or farmed) was

380 excluded using the two genotype datasets meaning that misassignment would be possible in this
381 scenario. When this individual was excluded from the sample dataset, there was no significant
382 difference in quantitative assignment scores between genotypes from RAD and Kasp approaches.
383 Neither sea bream nor sea bass exhibited discrepancies in population assignment, nor in
384 assignment scores, obtained with different sets of genotype data.

385 **Discussion**

386 The aim of the present work was to quantify the level of genetic information that can be obtained
387 with ddRAD approach, net of information loss during bioinformatic processing; and to evaluate
388 the performance of different bioinformatics approaches on the number of markers detected and
389 the precision of the genotype calling. The use of large datasets of marine fish species and the
390 application of the same approaches as those used in real case studies make our results
391 informative on the practical application of this technique.

392 *(i) Evaluation of sample representation within multiplexed libraries*

393 The first step in which genotyping information is lost is quality filtering, required to obtain
394 reliable results with NGS analysis (Minoche, Dohm, and Himmelbauer 2011; Bokulich et al.
395 2013). The filtering used in this work was stricter than the default of STACKS filtering, and
396 probably stricter than many of the filtering approaches used in population genetics studies.
397 However in this study our filtering process did not result in the loss of many samples; where
398 samples were removed this was mostly due to low initial read depth resulting from unequal
399 sequencing effort.

400

401 Relaxing the STACKs filtering parameters would be one method of retaining more reads,
402 however this would risk increasing genotyping error. An alternative approach, given that low

403 sequence quality is typically concentrated at the read ends, would be to employ further trimming
404 of all reads prior to commencing STACKS analysis. This should have the effect of retaining
405 more reads during subsequent STACKS filtering based on phred-scores. Nevertheless, this
406 procedure still causes loss of potentially high quality genetic information and a more efficient
407 approach would be to trim only those reads affected by low quality instead of trimming every
408 read to the same extent. This would only be possible if the downstream SNP caller program
409 allowed for different length reads (unlike STACKS).

410 One of the main advantages of RAD techniques is the possibility of multiplexing many
411 individuals in the same sequencing run thanks to individual sample barcoding. However, as the
412 number of multiplexed individual samples increases, the chance to have poorly represented
413 samples increases as well (Baird et al. 2008; Peterson et al. 2012), causing lower coverage and
414 in the worst case, too few reliably genotyped or false homozygote excess for a number of
415 individuals. In particular, the combination of samples at different quality/concentration, rather
416 than the quality itself of single samples, is the influencing variable (I.e. even using the exact
417 same starting DNA, result might vary in relation with the other samples genotyped in the same
418 library). The threshold at 150,000 raw reads used here is much lower than the expected average
419 number of reads per individual (1.3 millions) and may not be appropriate for other species. In
420 fact, it should be set taking into consideration the number of expected tag and the desired
421 average coverage depth. However, “losing” a certain amount of samples (up to 16% in our case)
422 needs to be considered when planning a ddRAD sequencing project, even when significant
423 effort was given to equalize DNA input under library preparation.

424 Not surprisingly, DNA quality was a good predictor of poorly performing samples (Graham et
425 al. 2015). Gel-based quality analysis essentially reflects the level of DNA degradation, that can

426 be caused by many factors that act before or after extraction. In our specific case, pre-extraction
427 factors are probably the most relevant, as extraction and post-extraction protocols were the same
428 for all the samples. Ethanol has been recognized as a good media for long term tissue storage
429 (Gillespie et al. 2002; Dawson, Raskoff, and Jacobs 1998), and it is easily available and not
430 hazardous. Nevertheless, Seutin, White, and Boag (1991) reported that ethanol conservation
431 can decrease DNA yield and cause significant degradation to the extracted DNA, that can be
432 reduced by keeping samples refrigerated as soon as possible after sampling. DNA from long-
433 term stored specimens might have some additional features reducing the efficiency in library
434 preparation. Therefore, when selecting the DNA samples to be pooled as part of the same library,
435 it is advisable to avoid mixing samples of heterogeneous DNA quality as well as mixing “fresh”
436 with “archived” specimens. When this is not possible (e.g. for those projects that use only one
437 or few sequencing pools), an upward correction for the starting amount of DNA of poor quality
438 samples and DNA from “archived” samples might be considered. However, further analysis is
439 necessary to better understand how this procedure should be applied.

440 (ii) *Tag length and coverage*

441 Accuracy and consistency in size selection is not easily achievable, but tag length distribution
442 was not significantly different across species in our study. From this point of view, the period
443 of training of the personnel proved to be effective in order to have consistent results.
444 Nevertheless, tags shorter than 190 bp were retained in our analysis, which was unexpected
445 considering that size selection step was implemented. Indeed, low accuracy has been
446 documented in particular for manual vs automated gel band extraction (Puritz 2015). A similar
447 result was found by DaCosta e Sorenson (2014), who recovered tags down to a length of 10 bp.
448 In our case, the purification steps performed at the very end of the library preparation protocol,

449 should eliminate most inserts shorter than 200 bp, that translates into RAD tags of 75 bp, after
450 removing adapters. It is important to notice that, considering the 100 bp paired-end sequencing
451 protocol used, all the analyzed fragments shorter than 190 bp are affected by Read1-Read2
452 overlapping of the final parts of the sequences, potentially causing SNP duplication, redundant
453 data and a waste of sequencing effort that further lower the actual power of ddRAD technique.
454 Improvement in size selection step is fundamental to optimize the performance of the ddRAD
455 technique.

456 Davey et al. (2013), using data from a *Caenorhabditis elegans* RAD library, found a strong
457 positive correlation between fragment length and coverage depth. In other published ddRAD
458 studies, such as DaCosta e Sorenson (2014), the relationship between coverage and length was
459 similar to our work. Tags with different lengths show variable coverage within individual
460 samples. This means that additional care should be taken when multiplex size is calculated, in
461 order to achieve a desired minimum depth of coverage across loci. According to our results,
462 loci in the shortest and longest length range will be underrepresented if coverage was calculated
463 just by dividing the number of individual reads by the number of expected loci. Upward
464 correction in the number of reads per individual should be applied to obtain minimum coverage
465 also for loci in short and long fragments.

466 (iii) *De novo and reference-based genotyping using STACKS*

467 The possibility to use RAD techniques in species without genomic resources (i.e. *de novo*
468 approach) has been highlighted as one of the method's biggest advantages (Willing et al. 2011;
469 Pegadaraju et al. 2013). However, we showed that using a reference genome improves RAD
470 genotyping performance, i.e. better precision and higher number of shared markers. With
471 reference based approach, only reads correctly mapped against the genome are used. Hence, the

472 quality of reference-based analysis is also dependent on the quality of the assembly used. In
473 particular, N50 seemed to better predict mapping percentage compared to average contig length.
474 Turbot shows the longest average contig length, but ranked second in terms of positive mapping
475 matches, in agreement with N50 ranking (Table 2). J. Catchen et al. (2013) showed that in
476 threespined stickleback *de novo* approach yielded a higher number of tags (42,300) than the
477 reference based one (37,600), mostly due to loss of loci that could not be mapped against the
478 reference genome (>4,700). Likewise, in our analysis, using the genome as a reference returned
479 a lower number of tags compared to the *de novo* approach (Table 3). In any case, the number
480 of *de novo*-based tags that mapped correctly to the reference genome was in good agreement
481 with the number of tags identified by the reference based analysis. The larger number of *de*
482 *novo* ddRAD tags might then be explained in part by the incomplete mapping of reads against
483 the reference genome as in the case of threespined stickleback. This seems reasonable
484 considering that the reference sequences used represent only a portion of the entire genomes of
485 the species. Indeed, compared to the genome lengths estimated from the c-values, from 70%
486 (turbot) to 85%(sea bream) of the entire genomes is represented in the references. So, at least
487 part of the *de novo* loci found could be real fragments of the genomes, coming from regions
488 that have been more difficult to sequence and assemble so far. A second possibility is that a
489 fraction of tags, which STACKS identified as separate “loci” in the *de novo* analysis, is likely
490 represented by divergent alleles of the same locus. However, STACKS controls for such
491 phenomenon through the $-M$ parameter and, in the present study, a less conservative value ($-$
492 $M=5$) than the default one ($-M=2$) was set for all species. More likely, *de novo* approach might
493 include some “spurious” loci at individual level. In support of this hypothesis, a filter that
494 exclude loci shared by less than 80% of individuals, filtered out most of *de novo* loci. The origin

495 of these tags is difficult to find but some sources can be the presence of exogenous DNA, e.g.
496 from viral/ bacterial contaminants or from other species. In fact, blasting the tags that did not
497 present matches with sea bream genome showed that around 20% of these tags could come
498 from virus, bacteria, human or from other species analyzed in the laboratory (data not shown).
499 Using a filter that prunes poorly shared loci would exclude these RAD. In any case, when using
500 a *de novo* approach, a further filter based on alignment of tags with potential contaminant
501 species should be implemented as it require little bioinformatic effort and reduces a potential
502 source of background noise in the results. In addition, we cannot exclude the presence of
503 sequencing errors introduced with amplification in library preparation and sequencing steps.
504 While we cannot exclude that these sequences can provide useful information or could be used
505 as dominant markers (Fu et al, 2013), we recognize that they need to be studied more in detail
506 to understand their origin and whether they can have bad effects on certain downstream
507 applications (i.e. those requiring the use of markers shared by a percentage of individuals).
508 Without deeper knowledge of the origin of these sequences, it is therefore advisable to use the
509 above mentioned filters to reduce source of bias in the final filtered datasets. In general, even if
510 in the form of a draft, a reference genome should allow more efficient SNP detection.

511 *(iv) Genotyping precision and error rates*

512 Genotyping reproducibility across technical replicates is one of the most important test to
513 evaluate genotyping methods. A first analysis on over 100 replicates over the three species
514 datasets, showed that “coverage” represented a significant explanatory variable for differences
515 in mismatch rates. In fact, sea bass’ technical replicates, which were characterized by a
516 significantly lower coverage, also showed lower precision than the two other species. The effect
517 of reduced coverage also appears to be affecting samples characterized by a high DNA quality.

518 Davey et al. (2011) suggested at least 30x average coverage depth for reference genome-based
519 analysis and at least 60x coverage depth for *de novo* analysis in order to obtain a complete
520 coverage of all restriction sites in a genome. In addition, Fountain (2016), based on Mendelian
521 inheritance incompatibilities, showed that genotyping errors decreased with increasing
522 coverage from 5x to 30x in both reference based and *de novo* datasets. In the present study, the
523 average coverage for all the three species was higher than that suggested in the studies
524 mentioned, but also the variability across loci was high (36x-386x in sea bass, 31x-2840x in
525 sea bream and 69x-2731x in turbot), which might influence the outcome in term of mismatch
526 rates. However, we couldn't find any significant correlation between mismatch rate and average
527 locus coverage when analyzing results within single datasets (i.e. "species+strategy").

528 The same analysis showed that the SNPs in the reference-based tags are more consistently
529 genotyped than *de novo* ones in both turbot and sea bream. The positive effect of using a
530 reference genome on genotyping reproducibility is an additional one to the advantage of
531 avoiding inflation of tag number described above. More reproducible genotypes are also
532 obtained when *a posteriori* genotype correction was implemented. Both approaches (reference-
533 based analysis and *a posteriori* correction) come at a price as the total number of tags/SNPs
534 analyzed gets reduced, so its use should be considered to obtain more reliable data according to
535 the aims of a particular project. Other issues deserve care when using genetic markers. On of
536 the most important is allelic dropout, that can lead to errors in population statistics, due to biased
537 heterozygosity estimates (Gautier et al., 2013). Some approaches have been proposed to detect
538 loci affected by allelic dropout, such as analysis of coverage, based on the expectation that
539 mutations within the restriction site would result in fewer reads being generated for one allele,
540 thus creating a bi-modal read depth distribution across loci (Cooke et al., 2016). Nevertheless,

541 a preliminary analysis of coverage distribution of our data didn't show the bi-modal distribution
542 expected with the high coverage obtained. This may be due to the fact that coverage also varies
543 with tag length, swamping any signal from allelic drop-out.

544 *Impact of genotyping accuracy on population assignment*

545 The average level of discrepancy between the test datasets used for the comparison was slightly
546 higher than the genotyping error recorded with the different ddRAD bioinformatic approaches,
547 but allowed us to detect the putative threshold at which genotyping imprecision starts affecting
548 downstream analysis, since we recorded both samples with and without assignment or allele
549 frequency deviations. In any case, levels of mismatch between replicates higher than those
550 found in this study (and approaching the threshold identified as causing deviation in
551 downstream analysis) are commonly found when using RAD genotyping (e.g. Forsström et al.
552 2017; Pecoraro et al. 2016). According to our results, the effect of sub-4 % genotyping
553 differences on allele frequency is not significant, while if variation increased (e.g. 4.8 % in sea
554 bream), the resulting allele frequencies were significantly different. Such findings are clearly
555 dependent on factors such as sample size and distribution of variation over loci, but do provide
556 an indication of the point at which genotype variation impacts allele frequency. Population
557 assignment was only affected when levels of genotyping variation were higher; the only
558 discrepancy being recorded for turbot where, despite displaying the lowest overall genotype
559 variation of the three species, one sample with three allele differences (8.3% of 36 alleles), was
560 assigned to different source populations. Again, such results will depend on which loci
561 displayed genotype variation and cannot be used in isolation to define threshold errors.
562 However, the finding does indicate the potential for realistic levels of genotype error to result
563 in significant changes to diagnostic results if not accounted for when evaluating the accuracy

564 of downstream applications.

565 **Conclusions**

566 Application of new genotyping techniques is rapidly increasing as they potentially allow more
567 accurate, easier and less expensive population genetic analysis of any species. However, several
568 issues might affect the quality of the results. In the present study, it was demonstrated that some
569 factors, i.e. DNA fragmentation and archived-fresh samples, affect the throughput in terms of
570 percentage and absolute number of high quality sequence reads in ddRAD datasets. Similarly,
571 actual fragment length and coverage can differ from expectations, leading to redundant loci and
572 loci with too low coverage. Although RAD has been proven to be applicable on non-model
573 species, the use of a preliminary draft genome sequence increase genotyping performance
574 enabling to obtain higher numbers of loci shared between multiplexed individuals. We highlight
575 the critical importance of introducing replicate individuals among samples to assess the
576 performance of the approach used and we demonstrate how variation in genotype datasets can
577 potentially impact the results of downstream population genetic applications. Our results are
578 useful for setting up genotyping project and for considering the features that can affect
579 genotyping throughput and precision.

580 **Data deposition**

581 Raw sequencing data are available at NCBI, with accession numbers SAMN7145243-7145512.

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590 **References**

- 591 Andrews, Kimberly R., Jeffrey M. Good, Michael R. Miller, Gordon Luikart, e Paul A.
592 Hohenlohe. 2016. «Harnessing the power of RADseq for ecological and evolutionary
593 genomics». *Nature Reviews Genetics* 17 (2): 81–92.
- 594 Arnold, B., R. B. Corbett-Detig, D. Hartl, e K. Bomblies. 2013. «RADseq underestimates
595 diversity and introduces genealogical biases due to nonrandom haplotype sampling».
596 *Molecular Ecology* 22 (11): 3179–90.
- 597 Baird, Nathan A., Paul D. Etter, Tressa S. Atwood, Mark C. Currey, Anthony L. Shiver,
598 Zachary A. Lewis, Eric U. Selker, William A. Cresko, e Eric A. Johnson. 2008.
599 «Rapid SNP discovery and genetic mapping using sequenced RAD markers». *PloS*
600 *one* 3 (10).
- 601 Bokulich, Nicholas A., Sathish Subramanian, Jeremiah J. Faith, Dirk Gevers, Jeffrey I.
602 Gordon, Rob Knight, David A. Mills, e J. Gregory Caporaso. 2013. «Quality-filtering
603 vastly improves diversity estimates from Illumina amplicon sequencing». *Nature*
604 *methods* 10 (1): 57–59.
- 605 Catchen, Julian, Paul A. Hohenlohe, Susan Bassham, Angel Amores, e William A. Cresko.
606 2013. «Stacks: an analysis tool set for population genomics». *Molecular ecology* 22
607 (11): 3124–40.
- 608 Catchen, Julian M., Angel Amores, Paul Hohenlohe, William Cresko, e John H. Postlethwait.
609 2011. «Stacks: building and genotyping loci de novo from short-read sequences». *G3:*
610 *Genes, Genomes, Genetics* 1 (3): 171–82.
- 611 Cooke, T. F., Yee, M. C., Muzzio, M., Sockell, A., Bell, R., Cornejo, O. E., ... & Kenny, E. E.
612 (2016). «GBStools: a statistical method for estimating allelic dropout in reduced

613 representation sequencing data». *PLoS genetics*, 12(2), e1005631.

614 Cruz, Vanessa P., Manuel Vera, Belén G. Pardo, John Taggart, Paulino Martinez, Claudio
615 Oliveira, e Fausto Foresti. 2016. «Identification and validation of single nucleotide
616 polymorphisms as tools to detect hybridization and population structure in freshwater
617 stingrays». *Molecular Ecology Resources*.

618 DaCosta, Jeffrey M., e Michael D. Sorenson. 2014. «Amplification biases and consistent
619 recovery of loci in a double-digest RAD-seq protocol».

620 Davey, J. W., Hohenlohe, P. A., Etter, P. D., Boone, J. Q., Catchen, J. M., & Blaxter, M. L.
621 (2011). «Genome-wide genetic marker discovery and genotyping using next-
622 generation sequencing». *Nature reviews. Genetics*, 12 (7): 499

623 Davey, John W., Timothée Cezard, Pablo Fuentes-Utrilla, Cathlene Eland, Karim Gharbi, e
624 Mark L. Blaxter. 2013. «Special features of RAD Sequencing data: implications for
625 genotyping». *Molecular Ecology* 22 (11): 3151–64.

626 Dawson, Mike N., Kevin A. Raskoff, e David K. Jacobs. 1998. «Field preservation of marine
627 invertebrate tissue for DNA analyses». *Molecular marine biology and biotechnology* 7
628 (2): 145–52.

629 Figueras, Antonio, Diego Robledo, André Corvelo, Miguel Hermida, Patricia Pereiro, Juan A.
630 Rubiolo, Jèssica Gómez-Garrido, Laia Carreté, Xabier Bello, e Marta Gut. 2016.
631 «Whole genome sequencing of turbot (*Scophthalmus maximus*; Pleuronectiformes): a
632 fish adapted to demersal life». *DNA Research*, dsw007.

633 Fountain, E. D., Pauli, J. N., Reid, B. N., Palsbøll, P. J., & Peery, M. Z. (2016). «Finding the
634 right coverage: the impact of coverage and sequence quality on single nucleotide
635 polymorphism genotyping error rates». *Molecular ecology resources*, 16 (4): 966-978

636 Forsström, T., Ahmad, F., & Vasemägi, A. (2017). «Invasion genomics: genotyping-by-
637 sequencing approach reveals regional genetic structure and signatures of temporal
638 selection in an introduced mud crab». *Marine Biology*, 164(9), 186

639 Fox, John. 2005. «Getting started with the R commander: a basic-statistics graphical user
640 interface to R». *Journal of statistical software* 14 (9): 1–42.

641 Gautier, M., Gharbi, K., Cezard, T., Foucaud, J., Kerdelhué, C., Pudlo, P., ... & Estoup, A.
642 (2013). «The effect of RAD allele dropout on the estimation of genetic variation
643 within and between populations». *Molecular Ecology*, 22 (11), 3165-3178.

644 Gillespie, John W., Carolyn JM Best, Verena E. Bichsel, Kristina A. Cole, Susan F. Greenhut,
645 Stephen M. Hewitt, Mamoun Ahram, Yvonne B. Gathright, Maria J. Merino, e Robert
646 L. Strausberg. 2002. «Evaluation of non-formalin tissue fixation for molecular
647 profiling studies». *The American journal of pathology* 160 (2): 449–57.

648 Gomes, I., A. Collins, C. Lonjou, N. S. Thomas, J. Wilkinson, M. Watson, e N. Morton. 1999.
649 «Hardy–Weinberg quality control». *Annals of human genetics* 63 (6): 535–38.

650 Graham, C. F., Glenn, T. C., McArthur, A. G., Boreham, D. R., Kieran, T., Lance, S.,
651 Manzon, R. G., Martino, J. A., Pierson, T., Rogers, S. M., Wilson, J. Y. and Somers,
652 C. M. 2015. Impacts of degraded DNA on restriction enzyme associated DNA
653 sequencing (RADSeq). *Molecular Ecology Resources* 15: 1304–1315.

654 Langmead, Ben, Cole Trapnell, Mihai Pop, e Steven L. Salzberg. 2009. «Ultrafast and
655 memory-efficient alignment of short DNA sequences to the human genome». *Genome*
656 *biol* 10 (3): R25.

657 Liu, Lin, Yinhu Li, Siliang Li, Ni Hu, Yimin He, Ray Pong, Danni Lin, Lihua Lu, e Maggie
658 Law. 2012. «Comparison of next-generation sequencing systems». *BioMed Research*

659 *International* 2012.

660 Mastretta-Yanes, A., Nils Arrigo, Nadir Alvarez, Tove H. Jorgensen, D. Piñero, e B. C.
661 Emerson. 2015. «Restriction site-associated DNA sequencing, genotyping error
662 estimation and de novo assembly optimization for population genetic inference».
663 *Molecular ecology resources* 15 (1): 28–41.

664 Minoche, André E., Juliane C. Dohm, e Heinz Himmelbauer. 2011. «Evaluation of genomic
665 high-throughput sequencing data generated on Illumina HiSeq and genome analyzer
666 systems». *Genome Biol* 12 (11): R112.

667 Narum, Shawn R., C. Alex Buerkle, John W. Davey, Michael R. Miller, e Paul A. Hohenlohe.
668 2013. «Genotyping-by-sequencing in ecological and conservation genomics».
669 *Molecular Ecology* 22 (11): 2841–47.

670 Pecoraro, C., Babbucci, M., Villamor, A., Franch, R., Papetti, C., Leroy, B., & Murua, H.
671 (2016). «Methodological assessment of 2b-RAD genotyping technique for population
672 structure inferences in yellowfin tuna (*Thunnus albacares*)». *Marine genomics*, 25, 43-
673 48

674 Pegadaraju, Venkatramana, Rick Nipper, Brent Hulke, Lili Qi, e Quentin Schultz. 2013. «De
675 novo sequencing of sunflower genome for SNP discovery using RAD (Restriction site
676 Associated DNA) approach». *BMC genomics* 14 (1): 556.

677 Peterson, Brant K., Jesse N. Weber, Emily H. Kay, Heidi S. Fisher, e Hopi E. Hoekstra. 2012.
678 «Double Digest RADseq: An Inexpensive Method for De Novo SNP Discovery and
679 Genotyping in Model and Non-Model Species». *PLoS ONE* 7 (5): e37135.
680 doi:10.1371/journal.pone.0037135.

681 Piry, Sylvain, Alapetite, A., Cornuet, J. M., Paetkau, D., Baudouin, L., & Estoup, A. (2004).

682 «GENECLASS2: a software for genetic assignment and first-generation migrant
683 detection». *Journal of heredity*, 95(6), 536-539

684 Puritz, Jonathan B. 2015. «Fishing for Selection, but Only Catching Bias: Examining Library
685 Effects in Double-Digest RAD Data in a Non-Model Marine Species». In *Plant and*
686 *Animal Genome XXIII Conference*. Plant and Animal Genome.

687 Puritz, Jonathan B., Mikhail V. Matz, Robert J. Toonen, Jesse N. Weber, Daniel I. Bolnick, e
688 Christopher E. Bird. 2014. «Demystifying the RAD fad». *Molecular ecology* 23 (24):
689 5937–42.

690 Seutin, Gilles, Bradley N. White, e Peter T. Boag. 1991. «Preservation of avian blood and
691 tissue samples for DNA analyses». *Canadian Journal of Zoology* 69 (1): 82–90.

692 Taberlet, Pierre, Sally Griffin, Benoît Goossens, Sophie Questiau, Valérie Manceau, Nathalie
693 Escaravage, Lisette P. Waits, e Jean Bouvet. 1996. «Reliable genotyping of samples
694 with very low DNA quantities using PCR». *Nucleic acids research* 24 (16): 3189–94.

695 Team, R. Core. 2013. «R: A language and environment for statistical computing».

696 Tine, Mbaye, Heiner Kuhl, Pierre-Alexandre Gagnaire, Bruno Louro, Erick Desmarais, Rute
697 ST Martins, Jochen Hecht, Florian Knaust, Khalid Belkhir, e Sven Klages. 2014.
698 «European sea bass genome and its variation provide insights into adaptation to
699 euryhalinity and speciation». *Nature communications* 5.

700 Wang, Shi, Eli Meyer, John K. McKay, e Mikhail V. Matz. 2012. «2b-RAD: A Simple and
701 Flexible Method for Genome-Wide Genotyping». *Nature Methods* 9 (8): 808–10.
702 doi:10.1038/nmeth.2023.

703 Willing, Eva-Maria, Margarete Hoffmann, Juliane D. Klein, Detlef Weigel, e Christine
704 Dreyer. 2011. «Paired-end RAD-seq for de novo assembly and marker design without

705 available reference». *Bioinformatics* 27 (16): 2187–93.

706 Xu, Jianfeng, Aubrey Turner, Joy Little, Eugene R. Bleecker, e Deborah A. Meyers. 2002.

707 «Positive results in association studies are associated with departure from Hardy-

708 Weinberg equilibrium: hint for genotyping error?» *Human genetics* 111 (6): 573–74.

709

Figure 1 Flowchart of the analysis pipeline followed in this study, indicating the results evaluated in order to understand the performances of ddRAD sequencing technique

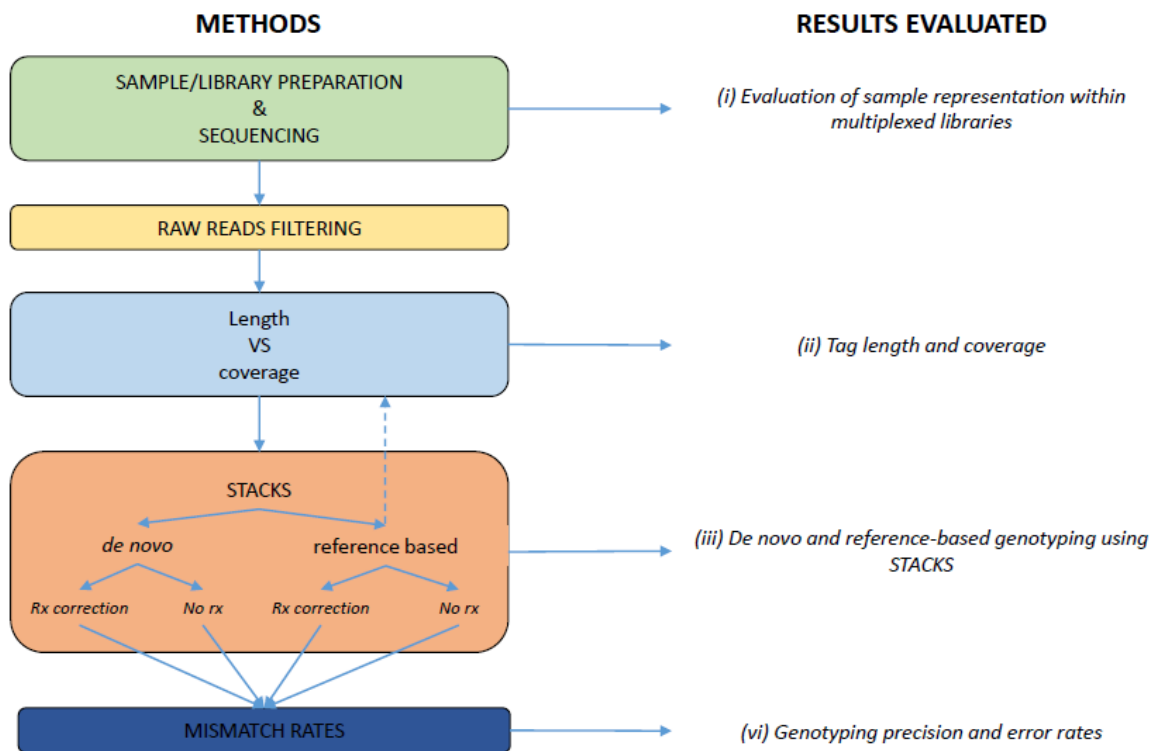


Figure 2: Graph of fragment length vs number of fragments in European sea bass (square), gilthead sea bream (diamond) and turbot (triangle). The graph is based on the reference-based analysis, as only for this it was possible to obtain information about fragments' length. Dash vertical line indicates the limit under which pair-end tags present overlapping between Read 1 and Read 2.

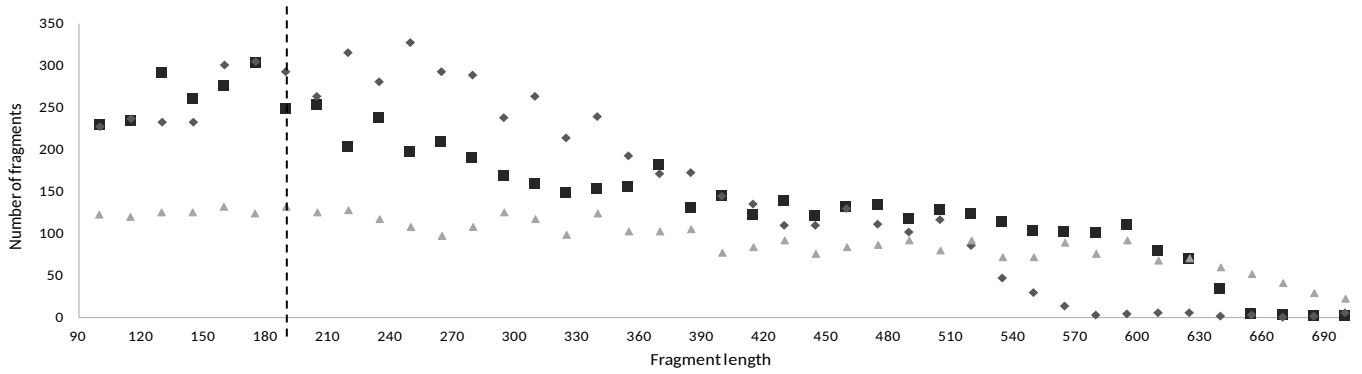


Figure 3: Graph of fragment length vs coverage depth in European sea bass (squares), gilthead sea bream (diamonds) and turbot (triangles). The graph is based on the reference-based analysis, as only here it was possible to obtain information about fragments' length. Coverage is expressed as relative to specific average coverage, in order to account for difference between species in average coverage depth. Trend lines were calculated as polynomial, third order for sea bass (solid line, $R^2=0.70$), sea bream (dash, $R^2=0.93$), turbot (point, $R^2=0.89$)

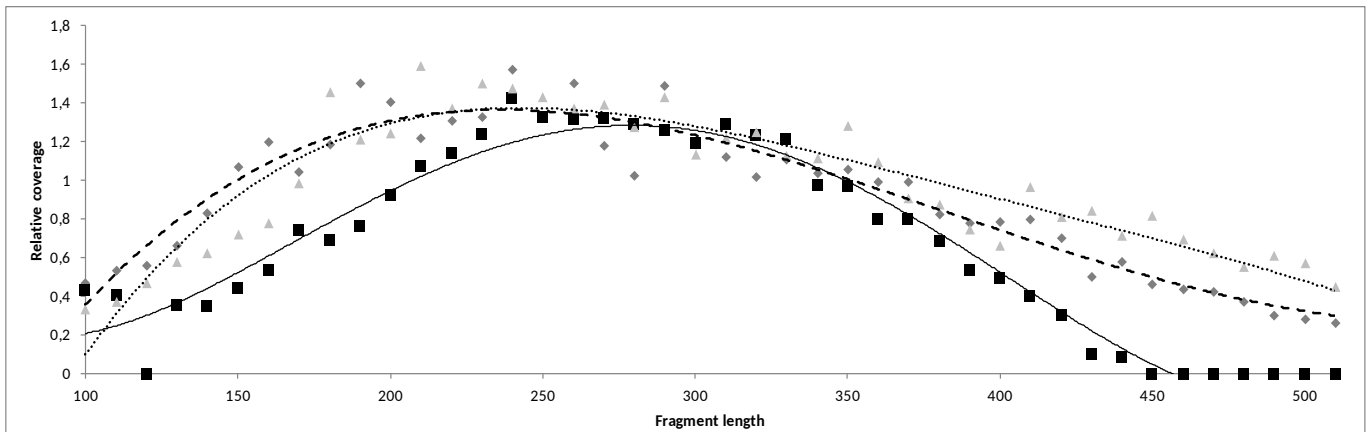


Table 1 Details of the genome resources used for European sea bass, gilthead sea bream and turbot.

Species	Length (Mbp)	N° of contigs	Average contig length	N50 (kbp)	Reference
European sea bass	668.3	37,783	17,687	62	Tine et al., 2014
Gilthead sea bream	770.3	259,783	2,965	13.35	Bargelloni et al., unpublished
Turbot	544.2	16,463	33,058	31.2	Figueras et al. 2016

Table 2 Summary of the STACKS' analyses on European sea bass, gilthead sea bream and turbot using de novo and reference based approaches. Application of the correction sub-program rxstacks is indicated under column 'Correction'. SNP frequency is calculated as the number of base pairs analyzed (180 bp x number of tags for the de novo approach; 90 bp x number of tags for the reference based approach) and the SNPs detected. 'Tags 80%' indicates the number of tags after filtering for those shared by at least 80% of individuals analyzed.

Species	Type of analysis	Correction	Tags	SNPs	SNP freq	Tags 80%	Average coverage
European sea bass	<i>de novo</i>	No correction	19,672	16,342	216.7	3,246	111.0 ± 65.9
		<i>rxstacks</i>	19,595	15,612	225.9	1,347	101.51 ± 59.6
	reference based	No correction	13,458	3,013	402.0	4,913	156.8 ± 94.3
		<i>rxstacks</i>	13,379	3,007	400.4	1,764	153.9 ± 92.9
Gilthead sea bream	<i>de novo</i>	No correction	25,322	39,842	114.4	3,913	151.5 ± 72.0
		<i>rxstacks</i>	24,257	31,790	137.3	2,353	89.3 ± 48.3
	reference based	No correction	13,659	5,161	238.2	7,091	247.7 ± 126.4
		<i>rxstacks</i>	12,293	4,388	252.1	5,796	109.9 ± 52.6
Turbot	<i>de novo</i>	No correction	58,171	26,635	393.1	1,674	272.1 ± 226.8
		<i>rxstacks</i>	56,320	21,582	469.7	1,631	157.3 ± 150.2

	No					700.9 ±
reference	correction	8,887	2,530	316.1	4,175	544.6
based	<i>rxstacks</i>	5,595	1,440	346.7	4,106	255.4 ±
						230.3

Table 3 Summary of mismatch analysis on European sea bass, gilthead sea bream and turbot using de novo and reference based approaches. Values are given as average or median percentage of genotypes that differ from the consensus (most frequently recorded) genotype over the total number of genotypes analyzed (number of individuals analyzed x number of SNPs). Application of correction subroutine rxstacks is indicated under column ‘Correction’.

Species	Type of analysis	Correction	Average % of mismatches	Median % of mismatches
Sea bass	<i>de novo</i>	No correction	2.9	0.9
		<i>rxstacks</i>	2.9	0.9
	reference based	No correction	1.9	0.5
		<i>rxstacks</i>	1.7	0.4
Sea bream	<i>de novo</i>	No correction	0.7	0.3
		<i>rxstacks</i>	1.3	0.3
	reference based	No correction	0.2	0.2
		<i>rxstacks</i>	0.1	0.1
Turbot	<i>de novo</i>	No correction	0.5	0.2
		<i>rxstacks</i>	0.6	0.1
	reference based	No correction	0.4	0.2
		<i>rxstacks</i>	0.3	0.1

1 **Performance and precision of double digestion RAD (ddRAD) genotyping in multiplexed datasets of**
2 **marine fish species**

3

4 **Supplementary Material**

5

6 Detailed library preparation protocol

7 Each group used biochemical consumables from the same manufacturers and were supplied with custom
8 barcoded ddRAD adapters mixes, sourced from the same original stocks prepared at the Institute of
9 Aquaculture, Stirling.

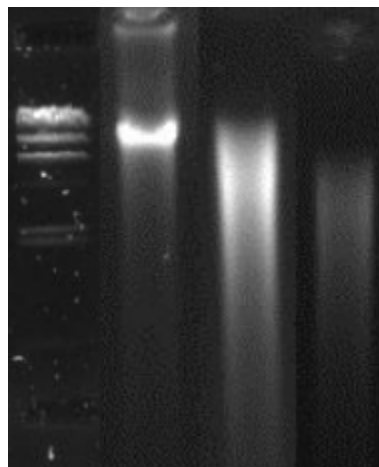
10 The original protocol of Peterson et al. (2012) involved processing each sample separately (i.e. restriction
11 digestion, adapter ligation, fragment size selection, PCR amplification and purification, quantitation) prior
12 to pooling into a single library for sequencing. A modified protocol (described in detail elsewhere;
13 Palaikostas et al. 2014; Manousaki et al. 2016), which was more convenient for screening large numbers of
14 individuals, was used for this project. The methodology allowed for pooling of samples after the adapter
15 ligation step, which greatly reduced the number of manipulations required, ensured consistent size
16 selection within libraries and reduced construction time to two to three working days. Library preparation
17 began with basic qualitative and quantitative assessment of extracted DNA samples. DNA quality was
18 evaluated by gel electrophoresis (0.8% agarose 0.5x TAE) and concentration was accurately measured by
19 fluorimetry with each sample being finally diluted to 7 ng/μL in 5 mM Tris pH 8.5. For a library (144
20 samples), individual DNA samples (21 ng) were first simultaneously digested with *SbfI* (recognition site
21 CCTGCA'GG) and *SphI* (recognition site GCATG'C) restriction enzymes, at 37° during 45 minutes. An adapter
22 mix comprising individual-specific barcoded combinations of P1 (*SbfI*-compatible) and P2 (*SphI*-compatible)
23 HPLC purified adapters (compatible with Illumina sequencing chemistry) were then added / ligated.
24 Adapters were designed such that adapter- genomic DNA ligations did not reconstitute RE sites, residual RE
25 activity limiting concatemerization of genomic fragments. Each adapter included an inline five- or seven-
26 base barcode, allowing for post-sequencing identification of individuals (P1-P2 combinatorial barcoding).
27 The ligation reactions were terminated by heat inactivation and all 144 samples combined in a single pool.

28 Following column purification of the pooled sample, DNA fragments in the range of 320 bp to 590 bp were
29 size selected by agarose gel electrophoresis, followed by gel-based column purification. The eluted size-
30 selected DNA template was then PCR amplified (14 cycles, 400 uL volume), column purified down to a 50 uL
31 volume and then subjected to a further clean-up using an equal volume of AMPure magnetic beads (Perkin-
32 Elmer, UK) (used in sea bream and turbot), to maximize removal of small fragments (less than ca. 200 bp).
33 The final library was eluted in c.20 μ L 10 mM Tris pH 8.5.

34 Libraries were sequenced on Illumina HiSeq 2500 sequencers with pair-end (PE) 100 base option to allow
35 sequencing of both barcodes at the Genomics Core of the University of Leuven, Belgium (sea bass and sea
36 bream) and BMR S.r.l, Padova, Italy (turbot).

37 DNA quality from agarose gel electrophoresis

Figure Example of “high” (a), “mid” (b) and “low” (c) quality DNA taken from agarose gel of DNA samples used in the study. On the leftmost well run 1 kb ladder.



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42 **References**

43 Manousaki, T., Tsakogiannis, A., Taggart, J. B., Palaiokostas, C., Tsaparis, D., Lagnel, J., & Tsigonopoulos, C. S.
44 (2016). Exploring a Nonmodel Teleost Genome Through RAD Sequencing—Linkage Mapping in Common
45 Pandora, *Pagellus erythrinus* and Comparative Genomic Analysis. *G3: Genes | Genomes | Genetics*, 6(3), 509-
46 519.

- 47 Palaiokostas, C., Bekaert, M., Khan, M. G., Taggart, J. B., Gharbi, K., McAndrew, B. J., & Penman, D. J. (2015).
48 A novel sex-determining QTL in Nile tilapia (*Oreochromis niloticus*). *BMC genomics*, 16(1), 171.
- 49 Peterson, B. K., Weber, J. N., Kay, E. H., Fisher, H. S., & Hoekstra, H. E. (2012). Double digest RADseq: an
50 inexpensive method for de novo SNP discovery and genotyping in model and non-model species. *PloS one*,
51 7(5), e37135.