



## Performance and precision of double digestion RAD (ddRAD) genotyping in large multiplexed datasets of marine fish species

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

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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, >2.5x10<sup>12</sup> 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  
77 methodologies, the authors recorded ddRAD-specific issues such as the recovery of restriction  
78 fragments shorter than expected, amplification bias toward GC-rich fragments, non-specific  
79 cutting by restriction enzymes, newly formed restriction enzyme sites and drop of fragment  
80 number due 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  
183 reference, we used the software package BOWTIE (Langmead et al. 2009), considering read  
184 pairing in the alignment process. We kept only read pairs that matched a single genomic  
185 position.

186 When building the RAD-tag catalog a maximum number of five mismatches between tags was  
187 set. For the reference-based approach, clustering was based on mapping position. Within a stack  
188 containing variant reads (i.e. potential SNPs), the following call thresholds were used: rare  
189 variant frequency (rvf)  $<0.01$  = homozygote;  $0.01 < rvf < 0.1$  = 'genotype unknown';  $rvf > 0.1$  =  
190 heterozygote called. *rxstacks*, STACKS' component that corrects genotypes on the basis of  
191 population information, was also implemented for comparison. Finally, we used the algorithm  
192 implemented in STACKS' *populations* step to retain only individual loci represented with at  
193 least 10 reads per individual sample and genotyped in at least 80% of the samples analyzed.  
194 This is an important step when the genotypes of multiple individuals need to be compared, as  
195 only shared loci provide useful information for genetic analysis.

196 *Analysis of the pipeline*

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

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

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

211 To identify the factors correlated with fewer reads, we tested the correlation between number  
212 of reads (above or below the threshold) and variables such as “DNA quality”, whether a sample  
213 was “fresh” or “archived”, “individual sample collector” (i.e. the project partner that collected  
214 the sample), and “index barcode” (different length/sequence barcodes could perform differently  
215 in the amplification or sequencing by synthesis steps), testing the effect of each variable under  
216 a Generalized Linear Model (GLM), as implemented in R 3.2.3 library function Rcmdr (Team  
217 2013; Fox 2005). Chi-squared tests were applied to check association between tested variables.

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

220 (ii) *Tag length and coverage*

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

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

234 In order to understand how the alignment to a reference genome influences SNP genotyping,  
235 we obtained individual genotypes using both *de novo* and reference-based analysis in STACKS.  
236 Since we expected *de novo* approach to detect also tags that are not contained in the reference  
237 genome, we wanted to evaluate the amount of *de novo* tags that could be found in the genome.  
238 In order to do this, RAD-tags resulting from *de novo* analysis (180 bp long) were subsequently  
239 split in two (in order to reconstitute the original 90 bp tags) and mapped against the reference  
240 genome using BOWTIE, with the same parameters used while aligning reads for reference based

241 analysis. Under both *de novo* and reference-based analysis, results were compared with and  
242 without the final step in *rxstacks*. Statistical differences between approaches were tested with  
243 chi-squared tests.

244 (iv) *Genotyping precision and error rates*

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

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

264 technique and bioinformatics protocols. Lastly, mismatch rates were analyzed across loci, to  
265 check the expectation that, within each “species+strategy” dataset (e.g. sea bream+*de novo* or  
266 turbot+reference based) loci with lower average coverage also showed higher mismatch rates.

#### 267 *Assessing the impact of genotyping accuracy*

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

287

## 288 **Results**

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

### 292 (i) *Evaluation of sample representation within multiplexed libraries*

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

308 After filtering and quality checking, the final number of replicated samples available for  
309 downstream analysis was 111: 43 sea bream samples (11 replicates for SAC3, 11 for SAC4, 10

310 for SAC5 and 11 for SAC6) genotyped across 11 independent libraries, 34 sea bass samples (5  
311 replicates for DLCTY\_40, 14 for DLT\_1 and 15 for DLM\_44) genotyped across 15 libraries  
312 and 34 turbot samples (9 replicates for SMFF1, 8 for SMFF2, 9 for SMFF3 and 8 for SMNS32)  
313 genotyped across 9 libraries.

314 (ii) *Tag length and coverage*

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

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

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

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

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

352 (iv) *Genotyping precision and error rates*

353 Our analysis suggested that “*rxstacks* correction” and “coverage” significantly affected the  
354 level of accuracy in the comparison of different approaches, regardless the species. In particular,  
355 lower mismatch rate were recorded when *rxstacks* was implemented and when coverage depth

356 per sample was higher. However, variation in mismatch rates were found between different  
357 species datasets (Table 3); they were apparently linked with differences in species-specific  
358 coverage, which varied significantly both for *de novo* RAD-tags (Kruskall-Wallis test,  $H=15.27$   
359  $p<0.001$ ) and reference-based ones (Kruskall-Wallis test,  $H=30.74$   $p<0.0001$ ). To overcome  
360 biases linked to species-specific differences, more specific tests were carried out within single  
361 datasets. In fact, additional factors were found to be significantly affecting mismatch rate. In  
362 addition to “*rxstacks* correction”, also “library”, “reference-mapping” and “sample” (only in  
363 the turbot database) showed significant correlations. At species level, “Coverage” showed a  
364 significant correlation in two out of three datasets (sea bream ( $p<0.05$ ) and turbot ( $p<0.001$ )).  
365 Nevertheless, across loci (i.e. within “single species+strategy” dataset) no significant  
366 correlation between mismatch and coverage was found.

#### 367 *Impact of genotyping accuracy on population assignment*

368 The percentage of samples with at least one different genotype observed in sea bass, sea bream  
369 and turbot was 31.5% (seven samples), 52% (13 samples) and 36% (eight samples), respectively,  
370 reflecting a total level of genotyping variation of 3.7% in sea bass (nine allelic differences), 4.8%  
371 in sea bream (eighteen allelic differences) and 3.0% in turbot (12 allelic differences). Resulting  
372 allele frequencies differed significantly at one locus in sea bream, that displayed the largest single  
373 allele frequency difference between the two genotype datasets (11.5%). A similar single locus  
374 deviation was observed in sea bass, despite the overall difference being non-significant. The effect  
375 of genotyping mismatch on individual assignment was lower; only for turbot, was one individual  
376 assigned to different populations of origin with the two genotype datasets. On closer inspection,  
377 the two genotypes for this sample differed at three alleles observed at two loci. The two genotypes  
378 at first locus were alternate homozygotes, whereas the other discrepancy was between

379 heterozygous and homozygous genotypes at another locus. Further analysis of the sample based  
380 on population exclusion testing revealed that neither population of origin (wild or farmed) was  
381 excluded using the two genotype datasets meaning that misassignment would be possible in this  
382 scenario. When this individual was excluded from the sample dataset, there was no significant  
383 difference in quantitative assignment scores between genotypes from RAD and Kasp approaches.  
384 Neither sea bream nor sea bass exhibited discrepancies in population assignment, nor in  
385 assignment scores, obtained with different sets of genotype data.

## 386 **Discussion**

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

### 393 (i) *Evaluation of sample representation within multiplexed libraries*

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

401

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

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

425 Not surprisingly, DNA quality was a good predictor of poorly performing samples (Graham et  
426 al. 2015). Gel-based quality analysis essentially reflects the level of DNA degradation, that can  
427 be caused by many factors that act before or after extraction. In our specific case, pre-extraction  
428 factors are probably the most relevant, as extraction and post-extraction protocols were the same  
429 for all the samples. Ethanol has been recognized as a good media for long term tissue storage  
430 (Gillespie et al. 2002; Dawson, Raskoff, and Jacobs 1998), and it is easily available and not  
431 hazardous. Nevertheless, Seutin, White, and Boag (1991) reported that ethanol conservation  
432 can decrease DNA yield and cause significant degradation to the extracted DNA, that can be  
433 reduced by keeping samples refrigerated as soon as possible after sampling. DNA from long-  
434 term stored specimens might have some additional features reducing the efficiency in library  
435 preparation. Therefore, when selecting the DNA samples to be pooled as part of the same  
436 library, it is advisable to avoid mixing samples of heterogeneous DNA quality as well as mixing  
437 “fresh” with “archived” specimens. When this is not possible (e.g. for those projects that use  
438 only one or few sequencing pools), an upward correction for the starting amount of DNA of  
439 poor quality samples and DNA from “archived” samples might be considered. However, further  
440 analysis is necessary to better understand how this procedure should be applied.

441 (ii) *Tag length and coverage*

442 Accuracy and consistency in size selection is not easily achievable, but tag length distribution  
443 was not significantly different across species in our study. From this point of view, the period  
444 of training of the personnel proved to be effective in order to have consistent results.  
445 Nevertheless, tags shorter than 190 bp were retained in our analysis, which was unexpected  
446 considering that size selection step was implemented. Indeed, low accuracy has been  
447 documented in particular for manual vs automated gel band extraction (Puritz 2015). A similar

448 result was found by DaCosta e Sorenson (2014), who recovered tags down to a length of 10 bp.  
449 In our case, the purification steps performed at the very end of the library preparation protocol,  
450 should eliminate most inserts shorter than 200 bp, that translates into RAD tags of 75 bp, after  
451 removing adapters. It is important to notice that, considering the 100 bp paired-end sequencing  
452 protocol used, all the analyzed fragments shorter than 190 bp are affected by Read1-Read2  
453 overlapping of the final parts of the sequences, potentially causing SNP duplication, redundant  
454 data and a waste of sequencing effort that further lower the actual power of ddRAD technique.  
455 Improvement in size selection step is fundamental to optimize the performance of the ddRAD  
456 technique.

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

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

468 The possibility to use RAD techniques in species without genomic resources (i.e. *de novo*  
469 approach) has been highlighted as one of the method's biggest advantages (Willing et al. 2011;  
470 Pegadaraju et al. 2013). However, we showed that using a reference genome improves RAD

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

494 include some “spurious” loci at individual level. In support of this hypothesis, a filter that  
495 exclude loci shared by less than 80% of individuals, filtered out most of *de novo* loci. The origin  
496 of these tags is difficult to find but some sources can be the presence of exogenous DNA, e.g.  
497 from viral/ bacterial contaminants or from other species. In fact, blasting the tags that did not  
498 present matches with sea bream genome showed that around 20% of these tags could come  
499 from virus, bacteria, human or from other species analyzed in the laboratory (data not shown).  
500 Using a filter that prunes poorly shared loci would exclude these RAD. In any case, when using  
501 a *de novo* approach, a further filter based on alignment of tags with potential contaminant  
502 species should be implemented as it require little bioinformatic effort and reduces a potential  
503 source of background noise in the results. In addition, we cannot exclude the presence of  
504 sequencing errors introduced with amplification in library preparation and sequencing steps.  
505 While we cannot exclude that these sequences can provide useful information or could be used  
506 as dominant markers (Fu et al, 2013), we recognize that they need to be studied more in detail  
507 to understand their origin and whether they can have bad effects on certain downstream  
508 applications (i.e. those requiring the use of markers shared by a percentage of individuals).  
509 Without deeper knowledge of the origin of these sequences, it is therefore advisable to use the  
510 above mentioned filters to reduce source of bias in the final filtered datasets. In general, even if  
511 in the form of a draft, a reference genome should allow more efficient SNP detection.

512 (iv) *Genotyping precision and error rates*

513 Genotyping reproducibility across technical replicates is one of the most important test to  
514 evaluate genotyping methods. A first analysis on over 100 replicates over the three species  
515 datasets, showed that “coverage” represented a significant explanatory variable for differences  
516 in mismatch rates. In fact, sea bass’ technical replicates, which were characterized by a

517 significantly lower coverage, also showed lower precision than the two other species. The effect  
518 of reduced coverage also appears to be affecting samples characterized by a high DNA quality.  
519 Davey et al. (2011) suggested at least 30x average coverage depth for reference genome-based  
520 analysis and at least 60x coverage depth for *de novo* analysis in order to obtain a complete  
521 coverage of all restriction sites in a genome. In addition, Fountain (2016), based on Mendelian  
522 inheritance incompatibilities, showed that genotyping errors decreased with increasing  
523 coverage from 5x to 30x in both reference based and *de novo* datasets. In the present study, the  
524 average coverage for all the three species was higher than that suggested in the studies  
525 mentioned, but also the variability across loci was high (36x-386x in sea bass, 31x-2840x in  
526 sea bream and 69x-2731x in turbot), which might influence the outcome in term of mismatch  
527 rates. However, we couldn't find any significant correlation between mismatch rate and average  
528 locus coverage when analyzing results within single datasets (i.e. "species+strategy").  
529 The same analysis showed that the SNPs in the reference-based tags are more consistently  
530 genotyped than *de novo* ones in both turbot and sea bream. The positive effect of using a  
531 reference genome on genotyping reproducibility is an additional one to the advantage of  
532 avoiding inflation of tag number described above. More reproducible genotypes are also  
533 obtained when *a posteriori* genotype correction was implemented. Both approaches (reference-  
534 based analysis and *a posteriori* correction) come at a price as the total number of tags/SNPs  
535 analyzed gets reduced, so its use should be considered to obtain more reliable data according to  
536 the aims of a particular project. Other issues deserve care when using genetic markers. One of  
537 the most important is allelic dropout, that can lead to errors in population statistics, due to biased  
538 heterozygosity estimates (Gautier et al., 2013). Some approaches have been proposed to detect  
539 loci affected by allelic dropout, such as analysis of coverage, based on the expectation that

540 mutations within the restriction site would result in fewer reads being generated for one allele,  
541 thus creating a bi-modal read depth distribution across loci (Cooke et al., 2016). Nevertheless,  
542 a preliminary analysis of coverage distribution of our data didn't show the bi-modal distribution  
543 expected with the high coverage obtained. This may be due to the fact that coverage also varies  
544 with tag length, swamping any signal from allelic drop-out.

#### 545 *Impact of genotyping accuracy on population assignment*

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

563 However, the finding does indicate the potential for realistic levels of genotype error to result  
564 in significant changes to diagnostic results if not accounted for when evaluating the accuracy  
565 of downstream applications.

## 566 **Conclusions**

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

## 581 **Data deposition**

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

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591 **References**

- 592 Andrews, Kimberly R., Jeffrey M. Good, Michael R. Miller, Gordon Luikart, e Paul A.  
593 Hohenlohe. 2016. «Harnessing the power of RADseq for ecological and evolutionary  
594 genomics». *Nature Reviews Genetics* 17 (2): 81–92.
- 595 Arnold, B., R. B. Corbett-Detig, D. Hartl, e K. Bomblies. 2013. «RADseq underestimates  
596 diversity and introduces genealogical biases due to nonrandom haplotype sampling».  
597 *Molecular Ecology* 22 (11): 3179–90.
- 598 Baird, Nathan A., Paul D. Etter, Tressa S. Atwood, Mark C. Currey, Anthony L. Shiver,  
599 Zachary A. Lewis, Eric U. Selker, William A. Cresko, e Eric A. Johnson. 2008.  
600 «Rapid SNP discovery and genetic mapping using sequenced RAD markers». *PLoS*  
601 *one* 3 (10).
- 602 Bokulich, Nicholas A., Sathish Subramanian, Jeremiah J. Faith, Dirk Gevers, Jeffrey I.  
603 Gordon, Rob Knight, David A. Mills, e J. Gregory Caporaso. 2013. «Quality-filtering  
604 vastly improves diversity estimates from Illumina amplicon sequencing». *Nature*  
605 *methods* 10 (1): 57–59.
- 606 Catchen, Julian, Paul A. Hohenlohe, Susan Bassham, Angel Amores, e William A. Cresko.  
607 2013. «Stacks: an analysis tool set for population genomics». *Molecular ecology* 22  
608 (11): 3124–40.
- 609 Catchen, Julian M., Angel Amores, Paul Hohenlohe, William Cresko, e John H. Postlethwait.  
610 2011. «Stacks: building and genotyping loci de novo from short-read sequences». *G3:*  
611 *Genes, Genomes, Genetics* 1 (3): 171–82.
- 612 Cooke, T. F., Yee, M. C., Muzzio, M., Sockell, A., Bell, R., Cornejo, O. E., ... & Kenny, E. E.  
613 (2016). «GBStools: a statistical method for estimating allelic dropout in reduced

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

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

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

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

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

627 Dawson, Mike N., Kevin A. Raskoff, e David K. Jacobs. 1998. «Field preservation of marine  
628 invertebrate tissue for DNA analyses». *Molecular marine biology and biotechnology* 7  
629 (2): 145–52.

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

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

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

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

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

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

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

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

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

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

660 *International* 2012.

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

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

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

671 Pecoraro, C., Babbucci, M., Villamor, A., Franch, R., Papetti, C., Leroy, B., & Murua, H.  
672 (2016). «Methodological assessment of 2b-RAD genotyping technique for population  
673 structure inferences in yellowfin tuna (*Thunnus albacares*)». *Marine genomics*, 25, 43-  
674 48

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

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

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

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

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

688 Puritz, Jonathan B., Mikhail V. Matz, Robert J. Toonen, Jesse N. Weber, Daniel I. Bolnick, e  
689           Christopher E. Bird. 2014. «Demystifying the RAD fad». *Molecular ecology* 23 (24):  
690           5937–42.

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

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

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

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

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

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

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

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

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

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

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