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Article type : Editorial

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Editorial note for Molecular Ecology

DNA metabarcoding - need for robust experimental designs to draw sound ecological conclusions

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This is the author manuscript accepted for publication and has undergone full peer review but has not been through the copyediting, typesetting, pagination and proofreading process, which may lead to differences between this version and the [Version of Record](#). Please cite this article as [doi: 10.1111/MEC.15060](https://doi.org/10.1111/MEC.15060)

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110 **Keywords:** environmental DNA (eDNA), experimental controls, replication, data quality

111 DNA metabarcoding, especially when coupled with high-throughput DNA sequencing, is
112 currently revolutionizing our capacity to assess biodiversity across a full range of taxa and habitats,
113 from soil microbes (e.g. Thompson et al., 2017) to large marine fish (e.g. Thomsen et al., 2016), and
114 from contemporary to tens of thousands year-old biological communities (e.g. Willerslev et al., 2003).
115 The breadth of potential applications is immense and spans surveys on the diversity or diet of species
116 native to specific ecosystems to bioindication (Pawlowski et al., 2018). The approach is also
117 especially cost-effective and easy to implement, which makes DNA metabarcoding one of the tools of
118 choice of the 21st century for fundamental research and the future of large-scale biodiversity
119 monitoring programs (reviewed in Bohan et al., 2017; Creer et al., 2016; Taberlet, Bonin, Zinger, &
120 Coissac, 2018; Thomsen & Willerslev, 2015). However, as is often the case with any emerging
121 technology, we feel that the rise of DNA metabarcoding is occurring at a pace and in a manner that
122 often loses sight of the challenges in producing high-quality and reproducible data (Baker, 2016).
123 DNA metabarcoding is by essence a multidisciplinary approach building upon many complementary
124 expertises, including field and theoretical knowledge, taxonomic expertise, molecular biology,
125 bioinformatics, and computational statistics. Combining all these within single studies is necessary,
126 not so much for producing and analyzing the data *per se*, but rather for minimizing and controlling the
127 possible biases that can be introduced at any step of the experimental workflow - i.e. from the
128 sampling to data analysis - and that can lead to spurious ecological conclusions (reviewed in Bálint et
129 al., 2016; Nilsson et al., 2019; Dickie et al., 2018; Taberlet et al., 2018).

130 Whether the starting material consists of DNA from bulk samples (community DNA) and/or
131 from environmental DNA (eDNA), all DNA metabarcoding studies rely on a deceptively simple
132 succession of core experimental steps: (i) sampling and preservation of the starting material, (ii),
133 DNA extraction, (iii) PCR amplification of a taxonomically-informative genomic region, (iv) high-
134 throughput DNA sequencing of the amplicons, and (v) sequence analysis using bioinformatic
135 pipelines. Despite this apparent simplicity, each step can potentially introduce its own sources of
136 artifacts and biases (Figure 1). For example, the sampling design might not be effective for capturing
137 the full taxonomic diversity or the ecological processes under study, an undesired bias for studies
138 based on species detection. The availability of DNA in the samples is governed by its production rate,
139 transport and persistence, processes which are all largely dependent on the targeted organisms, their
140 biomass, and the ecosystem considered. A correct assessment of an ecological phenomenon based on
141 DNA metabarcoding require not only implementation of standardized standardized, randomized and
142 repeatable sampling designs and procedures (Dickie et al., 2018), but also consideration of DNA
143 dynamics in the underlying matrix (i.e. in gut, feces, water or soil matrices from tropical or boreal
144 organisms/ecosystems; Barnes & Turner, 2016). Likewise, the community under study can be
145 enriched - on purpose or not - with specific taxa depending on how the sample is collected (e.g. filter
146 size for water samples, removal of roots or not for soils), how it is transported/preserved, and how
147 DNA is extracted (differential extraction efficiencies). PCR amplification is also well known to be an
148 important source of biases, that are now fully revealed with high-throughput DNA sequencing
149 techniques. The preferential amplification of certain taxa over other ones due to inappropriate primers
150 provides one such example of potential bias (Clarke, Soubrier, Weyrich, & Cooper, 2014; Deagle,
151 Jarman, Coissac, Pompanon, & Taberlet, 2014). Primer biases can both skew abundance profiles and
152 lead to false negatives. PCR amplification can produce false negatives too through the presence of e.g.
153 PCR inhibitors, but also many false positives through the introduction of replication errors by the
154 DNA polymerase or the formation of chimeric fragments (reviewed in Taberlet et al., 2018). False
155 positives can also be introduced at any step of the experimental workflow through the presence of
156 reagent contaminants (Salter et al., 2014), or through samples, extractions or PCR cross-
157 contaminations. An even more insidious source of false positives pertains to the occurrence of “tag
158 jumps”, sometimes referred to as “mistagging”, “tag-switching”, or “cross-talks” (Carlsen et al., 2012;
159 Edgar, 2018; Esling, Lejzerowicz, & Pawlowski, 2015; Schnell, Bohmann, & Gilbert, 2015). PCR
160 amplicons are indeed often tagged with unique short nucleotide sequences added on the 5'-end of the
161 primers (i.e. “tags”), which allow pooling all PCRs within a single sequencing run and reducing
162 sequencing costs. Each sequence obtained resulting in apparent cross-contaminations can then be
163 bioinformatically assigned back to its sample of origin on the basis of its tag (Schnell et al., 2015).
164 However, the procedures underlying the preparation of DNA libraries and/or the sequencing can
165 introduce these “tag jumps”, when the tag assigned to one particular sample is in fact recombined to
166 the sequences belonging to another sample (Taberlet et al., 2018). This introduces additional, non-

167 negligible levels of sample cross-contaminations, which primarily involve the most abundant taxa and
168 can have a disproportionate impact on samples with low DNA concentrations (Esling et al., 2015;
169 Murray, Coghlan, & Bunce, 2015; Schnell et al., 2015). Similarly, the Illumina index located on the
170 P5 sequencing adaptor can be subjected to “index jumps”, resulting in apparent cross-contaminations
171 (Taberlet et al., 2018). This bias happens when several individual Illumina sequencing libraries are
172 pooled and loaded on the same sequencing lane (Kircher, Sawyer, & Meyer, 2012) Finally, high-
173 throughput DNA sequencing instruments have their own error rates (Schirmer et al., 2015). The above
174 list of problems is clearly not exhaustive, and the interested reader will find more complete reviews
175 elsewhere (e.g. Bálint et al., 2016; Nilsson et al., 2019; Taberlet et al., 2018). Still, it illustrates that
176 any potential bias must be considered carefully when designing an experimental protocol and when
177 interpreting the results. This is crucial to limit their impact on downstream analyses, and to ensure that
178 the conclusion drawn from such data are authentic.

179 There is now an increasingly diverse range of field, laboratory (e.g. Caporaso et al., 2011;
180 Taberlet et al., 2018; Valentini et al., 2009) and bioinformatics (e.g. Boyer et al., 2016; Caporaso et
181 al., 2010; Dumbrell, Ferguson, & Clark, 2016) procedures aiming at reducing the amount of both false
182 negatives (i.e. due to partial sampling, extraction, amplification or sequencing bias) and false positives
183 (i.e. due to contaminations, “tag/index jumps”, or PCR and sequencing errors) in DNA metabarcoding
184 experiments. However, using these protocols does not necessarily guarantee that the problem of false
185 positives or negatives is completely under control. These protocols must continuously be
186 reconsidered, especially alongside the emergence of novel DNA sequencing technologies that provide
187 new opportunities, but also new challenges. Additionally, each individual study and each genomic
188 marker comes with its own specificities, and this often requires customization of the above protocols.
189 The sequence clustering threshold to be used to form molecular taxonomic units relevant to the
190 question addressed (e.g. removing intraspecific marker variability when the species level is desired)
191 provides such an example, and will critically depend on both the marker specificities and
192 PCR/sequencing error rates. Bioinformatics tools can further fail to exclude molecular artifacts when
193 the filtering thresholds are relaxed, which inflates sample diversity estimates. Likewise, they can also
194 generate false negatives, for example when a genuine metabarcode is falsely flagged as an error or
195 chimera, or when it is assigned to an incorrect taxon due to incomplete or inappropriate reference
196 databases (Alsos et al., 2018; Coissac, Riaz, & Puillandre, 2012). This can be especially problematic
197 when the question investigated strongly relies on species detection. It is therefore crucial to include
198 several types of experimental controls so as to facilitate the exclusion of spurious signal and support
199 the reliability of the biological conclusions (Figure 1). Amongst these controls, conducting pilot
200 experiments is particularly helpful to assess how appropriate the sampling design is (Dickie et al.,
201 2018). We also recommend that both biological replicates (i.e. multiple independent samples) and
202 technical replicates (i.e. multiple extractions/PCR of the same sample and/or extract) are included in

203 the experimental workflow to disentangle the effect of both the biological and technical variances
204 (Ficetola et al., 2015). These replications are necessary because both sampling and PCR can introduce
205 biases in a stochastic manner, especially when the concentration of the target DNA is low. It is also
206 essential to analyze a sufficient number of negative controls at the field sampling, DNA extraction,
207 PCR, and sequencing steps, as well as positive controls consisting of mock communities, known DNA
208 samples, or even synthetic sequences reflecting the attributes of the targeted products (Figure 1). All
209 these controls must be sequenced along the biological samples, as they facilitate the detection of
210 sporadic contaminations and tag or index jumps while helping adjusting filtering and clustering
211 thresholds. Ultimately, they will be a token of the reliability of the whole data curation process (De
212 Barba et al., 2014). We also encourage careful consideration of the bioinformatics workflow itself,
213 since the filtering steps necessary to curate the data will critically depend on the experimental design
214 and the ecological question under study. Typically, sequences of low abundance in a given sample
215 may be genuine or artifacts deriving from PCR/sequencing errors or tag/index jumps. The retained
216 filtering threshold for taxon presence is thus dependent on the underlying rates of artifacts, as well as
217 on the sequencing depth. As the different experimental controls provide direct measurements of these
218 artifacts, they will therefore allow better tuning of the filtering thresholds. All of these technical
219 considerations should be precisely reported within publications together with relevant illustrations and
220 statistics characterizing the workflow, as they are necessary to assess the relevance and quality of the
221 data underpinning specific conclusions. A last, a most obvious example of control consists in
222 assessing the plausibility of the taxonomic composition based on *a priori* knowledge of the system or
223 taxa studied. Such knowledge can be derived from data obtained with complementary sensing
224 approaches such as visual observations. In this case, building exhaustive local reference databases of
225 the genomic marker used from local specimens will secure the taxonomic assignment step (e.g. Alsos
226 et al., 2018). When local information is unavailable, typically when studying microorganisms, it
227 remains possible to assess whether the community is composed of clades that are expected to occur in
228 the system surveyed or not, as e.g. soils, sediments, and gut environments harbour highly different
229 bacterial phyla (e.g. Thompson et al., 2017).

230 As users, readers, referees or editors, we realize that the above-mentioned issues remain too
231 often overlooked. This problematic stance can lead to unsubstantiated claims and undermine scientific
232 advances if not resolved. Inappropriate practices such as estimating species richness from fingerprint
233 profiles (Bent, Pierson, & Forney, 2007), the absence of biological replicates (Prosser, 2010), or that
234 of contaminant controls (Perez-Muñoz, Arrieta, Ramer-Tait, & Walter, 2017) have been repeatedly
235 criticized in the field of microbial ecology, and in the latter case, they contribute to the rising debate
236 about the existence or not of a womb microbiota. Ancient DNA research has also developed rigorous
237 standards to tackle issues related to contamination, sequencing errors, and data reproducibility (Poinar
238 and Cooper (2000). We believe that the community of DNA metabarcoding users has now come of

239 age and learnt from its past errors. At a time when more and more exhaustive guides of best practices
240 on the subject are emerging (Knight et al., 2018; Pollock, Glendinning, Wisedchanwet, & Watson,
241 2018; Taberlet et al., 2018), and where DNA sequencing costs are rapidly decreasing, we should be
242 always mindful of the adage “better safe than sorry”. This note does not mean to imply that the
243 systematic use of the highest technical and analytical standards is reasonable nor the universal remedy
244 for all the challenges associated with DNA metabarcoding. Rather, we strongly encourage researchers
245 and end-users to adopt reflective decision-making when designing their experiment and to critically
246 appraise their results, with the ultimate aim to prove the robustness and reproducibility of their
247 conclusions.

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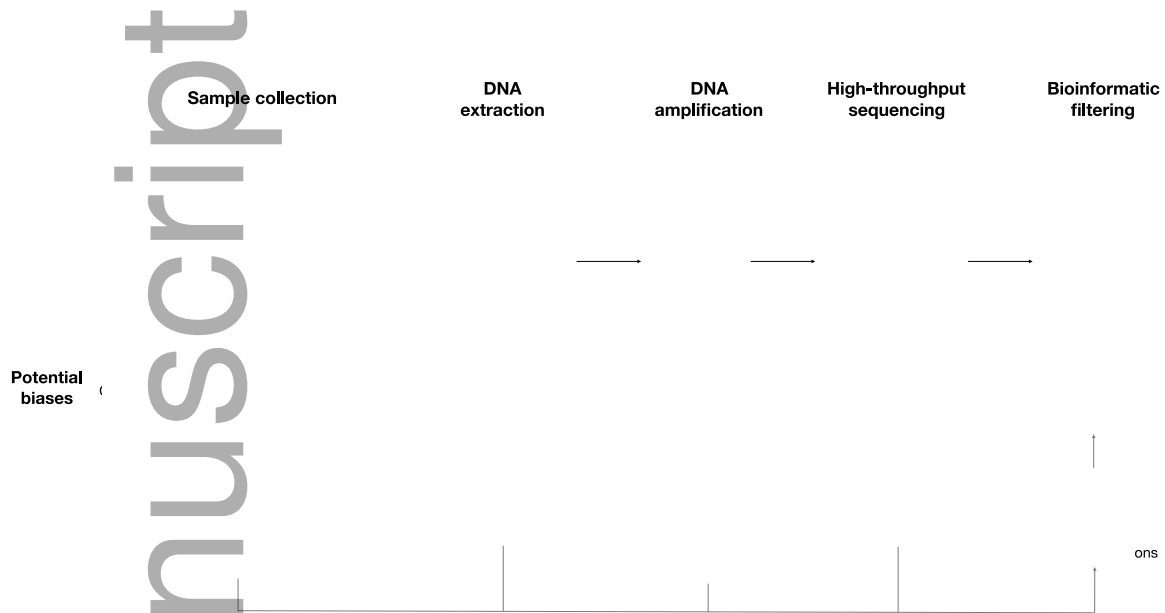
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354 **Figure 1 Summarized workflow of DNA metabarcoding and biases in the data production**
355 **process, with the potential associated controls to assess data quality.** Expectations on the local
356 community, either from a priori knowledge on the site or organisms targeted, or obtained through e.g.
357 vizual census, specimen collection, or building of a local reference database, constitute a first
358 assessment of the DNA metabarcoding experiment success. Pilot experiments are essential for
359 optimizing the whole experimental design, from the sampling strategy (e.g. number of biological
360 replicates) to the entire technical approach. Field, extraction, PCR, and tagging-system negative and
361 positive controls should be sequenced along with biological samples. They all aim at identifying (i)
362 potential contaminants that could be introduced at any experimental step, and (ii) potential
363 experimental artifacts due to the DNA extraction, PCR, and sequencing steps. Field negative controls
364 consists of extracting DNA from storage/extraction buffers brought to the field or used to clean
365 sampling instruments. Tagging-system negative controls can only be implemented when amplicons
366 are identified by a unique combination of tags attached to the 5' end of each amplification primer, and
367 where one or several tag combinations remain unused in the experimental design. In such conditions,
368 tagging-system controls can be performed at the bioinformatics analysis step, by monitoring the
369 number of sequences harboring unexpected tag combinations. This number is actually a direct
370 measurement of the tag-jump rate. “Index jumps” are more difficult to evaluate, and can be controlled
371 either by indexing both library adapters (P5 and P7) or when the libraries sequenced together have

372 identifiable sequences that could indicate their origin. The positive controls (constructed using either
373 synthetic DNA with the primer target sequences on both sides, DNA extracted from a mock
374 community, or known environmental samples), as well as prior expectations on the taxa that should
375 occur in the system can be used to evaluate the effectiveness of the data production process, the
376 impact of contaminants on the retrieved ecological signal and the adequacy of bioinformatics filtering
377 procedures.

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