Taxonomic identification from metagenomic and metabarcoding data using any genetic marker

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Correct taxonomic identification of DNA sequences is central to studies of biodiversity using both shotgun metagenomic and metabarcoding approaches. However, there is no genetic marker that gives sufficient performance across all the biological kingdoms, hampering studies of taxonomic diversity in many groups of organisms. We here present a major update to Metaxa2 (http://microbiology.se/software/metaxa2/) that enables the use of any genetic marker for taxonomic classification of metagenome and amplicon sequence data.

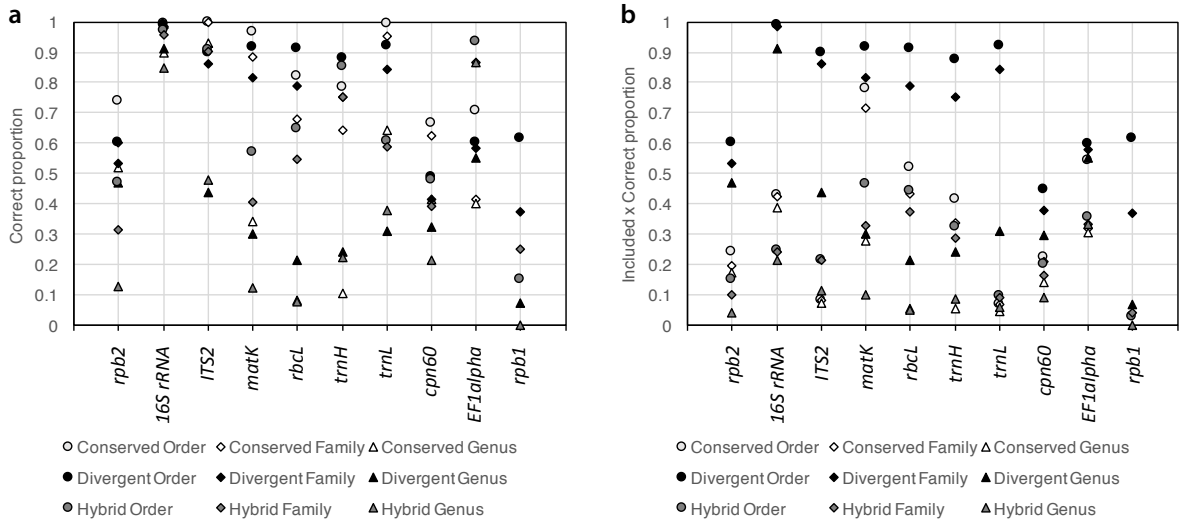
Sequencing of DNA has revolutionized taxonomy, providing unprecedented resolution for species identification and definition[1,2]. Similarly, the advent of large-scale sequencing techniques has opened entirely new windows on ecology, both for microbes and multicellular species[3]. In particular, high-throughput assignment of species and genus designations based on mixed samples of organisms or environmental substrates, so called DNA metabarcoding[4], has made it possible to perform fine-tuned investigations of taxonomic diversity and to understand ecological interactions in different types of environments. However, an important bottleneck in such analyses is the size and quality of the reference sequence data to which the newly generated sequence reads are compared[5,6]. Furthermore, while the ribosomal small-subunit (16S/18S/SSU) is a popular marker choice, no single genetic marker seems to be sufficient for covering all taxonomic groups with satisfactory accuracy for species or even genus assignments[7-9]. This has led to the establishment of a wide range of other genetic markers for DNA barcoding and metabarcoding in different organisms, such as *rbcL*, *matK*, *trnL,* and *trnH* for plants[10], the ITS region for fungi[11], and the COI gene for animals[12]. This broad diversity of DNA barcodes challenges sequence classification tools, which usually have been developed with the rRNA genes

59 in mind[13-15]. Although some of these software tools can be re-trained on other reference datasets,
60 or have their reference databases exchanged for datasets representing other genes, they still make
61 assumptions with regards to the reference data – such as global alignability – that often negatively
62 affect performance, or prevent software operation altogether. In addition, increasing stringency
63 with regards to correct taxonomic assignment often comes at the cost of lower proportions of
64 classified sequences[16]. This tendency has been shown for some taxonomic classifiers also when
65 operating on the rRNA genes[17]. The classification tool that appear least prone to show such a
66 relationship is Metaxa2, which is based on a combination of hidden Markov models (HMMs) and
67 sequence alignments[17]. Metaxa2 examines arbitrary DNA sequence datasets, such as genomes,
68 metagenomes, or amplicons, and extracts the SSU and/or LSU rRNA genes; classifies the
69 sequences to taxonomic origin; and optionally computes a range of diversity estimates for the
70 studied community. However, Metaxa2 has so far been strictly limited to operation on the rRNA
71 genes, preventing its use for other DNA barcodes. Yet, the capability of Metaxa2 to achieve high
72 precision for its classifications while maintaining relatively high sensitivity would be highly
73 desirable also for other genetic markers, particularly as these genes often are under-sampled in
74 terms of species coverage[16]. Against this backdrop, the aim of this study was to adapt the
75 Metaxa2 software for any additional DNA barcode. To this end, the paper presents an update to
76 Metaxa2 itself, allowing the use of custom databases. We also introduce the Metaxa2 Database
77 Builder – a software tool that allows users to create customized databases from DNA sequences
78 and their associated taxonomic affiliations – and a repository for additional reference sets to meet
79 the needs of the user.

80 The Metaxa2 Database builder has three different operating modes. The divergent mode is
81 adapted to deal with barcoding regions for which fairly large sequence variability occurs among
82 the target taxa, such as the eukaryotic ITS region[18], the *trnH* gene used in plant barcoding[16] and
83 the COI gene used, e.g., for insects[12]. The conserved mode, on the other hand, is suitable for
84 barcoding regions that are highly conserved among the target taxa, such as the SSU rRNA genes[19]
85 and the bacterial *rpoB* gene[20]. In addition, this mode is advisable for certain barcoding genes used
86 in narrower taxonomic groups, such as Oomycota. In the conserved mode, the software extracts
87 the barcoding regions from every input sequence and aligns them in order to determine the level
88 of conservation across every position in the alignment. The most conserved regions are then
89 extracted from the alignment and used to build HMMs that can be used to extract the barcoding
90 region from metagenomic data. In the divergent mode, the database builder instead clusters the
91 input sequences, aligns every individual cluster and builds one HMM for each cluster. The third
92 mode – the hybrid mode – combines the features and advantages of the two others, but also their
93 drawbacks. It should therefore only be used when none of those produces satisfactory results.

94 A key component for the high accuracy of Metaxa2 is the hand-curated classification database[17].
95 In the database builder, we have tried to emulate this curation by automating as much of our
96 procedure as possible. There are three ways in which the software attempts to improve the
97 taxonomic information. First, it can remove uninformative sequences from unknown specimens
98 or mixed environmental samples. Second, it can make an effort to standardize the input
99 taxonomy into seven levels. Finally, it can filter out entries without taxonomic affiliation at, for
100 example, the genus or species level.

101 We evaluated the Metaxa2 Database Builder on 11 different barcoding regions, targeting a variety
102 of uses (Supplementary Table 1). We first assessed the software performance on full-length
103 sequences using the self-evaluation function, measured in terms of sensitivity, specificity, and
104 error per assignment rate (Supplementary Fig. 1, see methods for details). In general, we found
105 that at least one of the methods produced more than 80% correct assignments at the family level
106 for half of the markers (Fig. 1a). However, three of the genetic markers – *rpb1*, *rpb2* and *cpn60* –
107 consistently showed lower performance across all groups, even at the order level. When we
108 multiplied the proportion of correct assignments with the total proportion of sequences assigned,
109 it was clear that the divergent mode consistently was the best performing setting by this measure
110 (Fig. 1b), mostly because the divergent mode always included the largest proportion of the input
111 sequences in the final database (Supplementary Fig. 2). However, since the divergent mode
112 includes essentially all input sequences in the classification database, it necessitates more careful
113 manual curation of the dataset used for database creation. Therefore, if the data at hand is of
114 uncertain quality, it may still be more adequate to use the conserved mode.



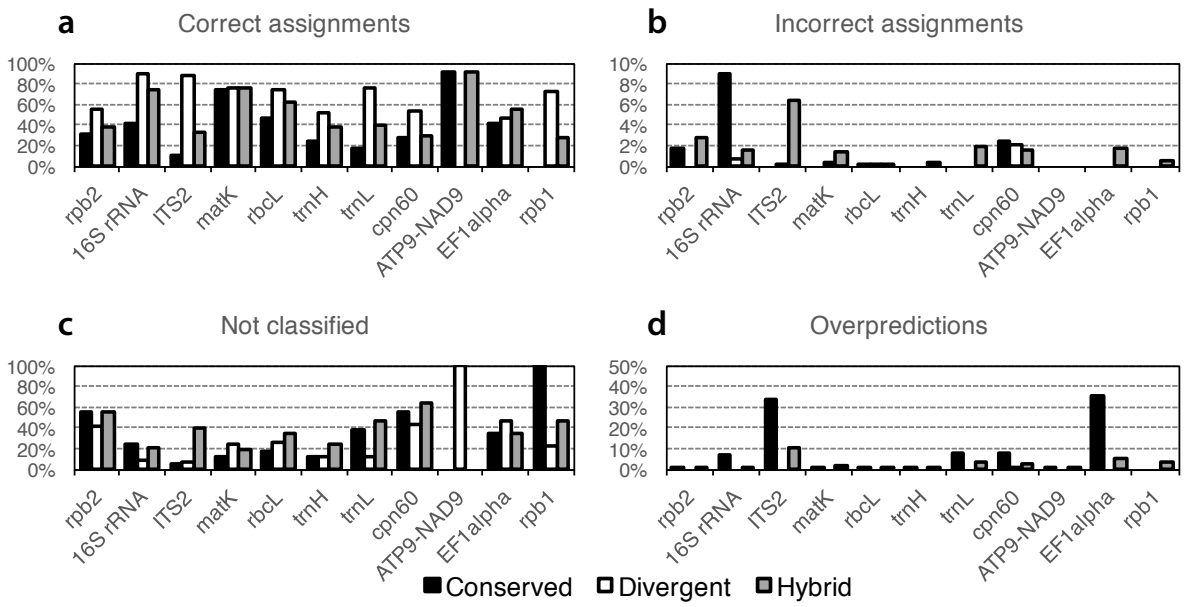
115

116 **Fig. 1.** Self-evaluated performance of the Metaxa2 Database Builder in different operating modes (conserved,
117 divergent and hybrid) on ten different DNA barcoding regions. A) Proportion of assigned sequences classified to the
118 correct order (circles), family (diamonds) and genera (triangles). B) Proportion of correctly assigned sequences
119 multiplied with the proportion of sequences included in the final classification databases (see Supplementary Fig. 2).
120 The ATP9-NAD9 genetic marker is not shown, because it only had relevant taxonomic differences at the species
121 level.

122

123 As an additional performance assessment, we followed the procedure from the original Metaxa2
124 evaluation[17] and generated fragments of 150 nucleotides from each barcoding region to estimate
125 the performance on shotgun metagenomic data. Here, we found that for most regions, the
126 divergent mode generated the highest proportion of correct classifications (Fig. 2a). For
127 EF1alpha, the hybrid mode performed better, for *matK* the operating modes were essentially tied,
128 and for ATP9-NAD9 the conserved and hybrid modes performed the best. However, the
129 divergent mode also produced higher numbers of misclassifications than the conserved mode did
130 for ITS2, *matK* and *rbcL*, although the hybrid mode showed the largest numbers of incorrect
131 assignments overall (Fig. 2b). Generally, the divergent mode showed the lowest levels of
132 unclassified input sequences and over-predictions (Fig. 2c, 2d). Still, there are obvious differences
133 in performance between different genetic markers. Particularly, it seems to be difficult to build
134 appropriate models for the *rpb* genes and *cpn60*, at least based on the sequence data we used.
135 Depending on what the user values the highest (comprehensiveness, stringency, precision etc.),
136 different settings would be desirable, and several combinations of modes and filtering options
137 should be evaluated against each other to find the optimal settings for each genetic marker and
138 reference dataset. We furthermore compared the evaluation of the fragments to the internal
139 software evaluation for each dataset (Supplementary Fig. 3). We found an essentially linear
140 relationship between the proportion of sequences included in the database times the proportion

141 of correct sequences in the internal evaluation and the proportion of correctly assigned sequence
142 fragments (Supplementary Fig. 3e), and thus this may provide a robust measure of overall
143 database performance.



144

145 **Fig. 2.** Family level Metaxa2 performance on randomly generated 150 bp fragments originating from the sequence datasets used
146 to build the respective databases in the three different modes (Conserved, Divergent and Hybrid). A) Proportions of fragments
147 assigned to the correct taxonomic family. B) Proportions of fragments assigned to an incorrect family. C) Proportions of
148 fragments not assigned, or not recognized as belonging to the investigated barcoding region, at the family level. D) Family-level
149 overpredictions, i.e. the proportions of sequence fragments belonging to a family not present in the final database, which were
150 still assigned to a (different) family by Metaxa2. Note that the ATP9-NAD9 dataset is only used for species identification and thus
151 this marker would be expected to show perfect performance on the family level. Note also that the Y-axis scales are different for
152 B and for D compared to A and B.

153 We also compared the classification performance of the native Metaxa2 database to those
154 resulting from automated construction based on SILVA. We built databases from release 111
155 (which was used as a starting point for the native Metaxa2 database) and release 128 in the
156 conserved mode, with two versions for each release; one in which no filtering was applied and
157 one in which we applied the filtering designed to mimic the manual curation process. We then
158 classified simulated SSU fragments using Metaxa2, replacing the native database with the newly

built ones. Overall, the results were surprisingly similar (Supplementary Fig. 4), contrary to what was previously shown when the native database was replaced with the GreenGenes database[17]. Interestingly, there were also rather small differences between the non-filtered and the automatically filtered databases, although applying filtering increased the number of classified sequence fragments with full taxonomic annotation and lowered the proportion of incorrect assignments, particularly at short fragment lengths. This indicates that the automated approach to database building is feasible, at least when the underlying sequence and taxonomy data are of high quality.

Evaluations of which taxonomic classification tools show the most consistent performance in terms of sensitivity and specificity are still largely incomplete[21], particularly for non-standard barcoding regions, but commonly used software for taxonomic assignment, such as the RDP Naïve Bayesian Classifier[13] and Rtax[14], have all been shown to perform subpar or inconsistently in different settings[15-17]. We believe that the lack of comprehensive evaluation does not excuse the use of methods that produce incorrect or irrelevant results. With decreasing cost of DNA sequencing and increasing use of shotgun metagenomics for studies of biological communities, these updates to the Metaxa2 software – vastly extending its capabilities to virtually any high-quality DNA barcode in use – will enable a leap forward for molecular ecologists and others in need of precise taxonomic assignment among groups of taxa that are not feasibly targeted by traditional barcoding markers.

179 ## Methods

180 **Software implementation**. The Metaxa2 Database Builder (metaxa2_dbb) is a command-line,
181 open source, Unix/Linux tool implemented in Perl. The software requires, on top of Perl, the
182 Metaxa2[17], HMMER3[22], NCBI BLAST[23], and MAFFT[24] software to be installed. In addition,
183 USEARCH[25] or VSEARCH[26] is highly recommended for full functionality. In short, the
184 metaxa2_dbb tool creates the hidden Markov models (HMMs) and BLAST reference databases
185 required to build a custom Metaxa2 classification database. Importantly, metaxa2_dbb can be run
186 in three different operating modes, depending on how similar the sequences in the reference
187 database are to each other.

188 In the conserved mode, used when sequences have regions of relatively high sequence similarity,
189 the software first identifies a suitable main reference sequence, either by user selection or by
190 clustering the sequences at 80% identity using USEARCH, and then selecting the representative
191 sequence of the largest cluster. Next, it uses the (5') start and (3') end of the main reference
192 sequence to define which of the other sequences in the input dataset should be considered full-
193 length, and extracts those regions using Metaxa2. Thereafter, the identified full-length sequences
194 are aligned using MAFFT, and the regions outside of the start and end of the main reference
195 sequence are trimmed away before re-aligning the trimmed sequences again. This alignment is
196 then used to determine the degree of sequence conservation across the alignment, to identify the
197 regions of high and low conservation. The conserved regions of the alignment are extracted and
198 aligned individually using MAFFT. Those alignments are used to build separate HMMs for each
199 conserved region with hmmbuild of the HMMER package. The full-length input sequences
200 matching at least half of those HMMs are then used to build the BLAST database used for

classification, and their sequence IDs are edited to be compatible with the Metaxa2 database structure.

In the divergent mode, the input sequences are first clustered into groups with at least 20% sequence identity using USEARCH. Each such cluster is then aligned separately using MAFFT. The alignments are subsequently split at the mid position (including gaps), and each pair of alignments is used to build two separate HMMs using hmmbuild. The input sequences matching at least one of those HMMs are then used to build the BLAST database for classification, and their sequence IDs are edited as above. The hybrid mode is a combination of the conserved and divergent modes, in which the database builder will cluster the input sequences at 20% identity using USEARCH, and then proceed with same approach as in the conserved mode on each resulting cluster separately.

From this point, the analysis proceeds identically for the three modes. The software reads taxonomy data in any of the following formats: ASN.1, NCBI XML, and INSD XML formats, as provided by GenBank[27]; FASTA format with taxonomy data as part of the sequence headers, as provided by the SILVA[28] and Greengenes[29] databases; and the Metaxa2 tabulated taxonomy format. Optionally, the taxonomy data can be filtered to exclude sequences from uncultured or unknown organisms or with low-resolution taxonomic annotation information. The sequence data and taxonomic information are subsequently crosschecked such that entries are only retained if both sequence and taxonomy data are present. The remaining sequences are then compiled into a BLAST database using formatdb or makeblastdb of the BLAST/BLAST+ packages. Thereafter, unless pre-determined sequence identity cutoffs are provided by the user, suitable identity thresholds for taxonomic assignments at different classification levels are

223 automatically determined. This is done by aligning the sequences in the BLAST database using
224 MAFFT and then calculating the pairwise percent identity within and between taxonomic groups
225 (intra- and inter-specific sequence identity). The identity cutoff for each taxonomic level is then
226 set to be below the lowest intra-specific pairwise identity and, if possible, above the highest inter-
227 specific pairwise identity. The cutoff can never be set to be above 99% identity for any
228 taxonomic level.

229 Finally, the metaxa2_dbb software can perform an optional database evaluation step, which is
230 further described below. A more thorough description of the database construction process can
231 be found in the software manual (Supplementary Item 1). It should also be noted that to make
232 the Metaxa2 classifier more reliable across a variety of barcoding regions, we have modified the
233 algorithm for assigning reliability scores (see the manual for details; Supplementary Item 1).
234 These modifications in general have very little effect on SSU and LSU classifications, but can
235 nevertheless result in slight differences when the same dataset is classified using this version of
236 Metaxa2 and versions prior to 2.2.

237 **Automatic correction of taxonomic data**. If the user chooses, metaxa2_dbb can attempt to
238 adjust the supplied taxonomy data in order to better match the taxonomic levels to those
239 proposed by the Metaxa2 software (domain, phylum/kingdom, class, order, family, genus,
240 species, and strain/subspecies). The phylum level is sorted out first, by checking which input
241 taxonomic level that corresponds to a list of recognized phyla/kingdoms. This is followed by
242 searching for a taxonomic level below the phylum level with an annotation ending with "-ales" to
243 define the order level (unless the entry seems to be of metazoan origin). Then, the class level is
244 defined as the level above the order level, and the family level is defined as the first level below

245 the order level and with an annotation ending with "-ceae" (or "-idae" for metazoans). The
246 species level is then identified by finding a taxonomic annotation similar to a Latin binomial
247 using regular expressions. The genus level is finally defined as the level containing the genus part
248 of the Latin binomial. This procedure can correct the vast majority of inconsistent taxonomic
249 annotation data, although manual curation of the output data is highly recommended to catch
250 exceptional cases.

251 **Use cases and software evaluation**. We evaluated the metaxa2_dbb software by providing 12
252 different use cases involving 11 different DNA barcodes used in different scenarios
253 (Supplementary Table 1). Notably, the datasets used to evaluate the software were not collected
254 for the specific purpose of this evaluation, but were rather typical representatives of reference
255 datasets used in previous or ongoing studies, thereby representing realistically relevant use cases
256 for the Metaxa2 Database Builder very well. For the ITS2, *matK*, *rbcL*, *trnL* and *trnH* genetic
257 markers, references were obtained from Richardson et al. (2017)[16]. Briefly, all NCBI nucleotide
258 sequences for vascular plant available on 2016-03-04 were downloaded, filtered by length, and all
259 sequences with more than two sequential uncalled nucleotides were removed. The datasets were
260 then filtered to remove duplicates and sequences from plants not present in Ohio and
261 surrounding states and provinces. Taxonomic information was obtained from NCBI taxonomy[30].
262 Sequences with undefined taxonomic information at any rank were removed. For *rpb1*, *rpb2* and
263 *EFalpha*, references were obtained from the fungal six-gene phylogeny of James et al.[31]. Sequence
264 data and taxonomic information were obtained from NCBI. For the 16S rRNA gene, sequences
265 and taxonomic data for type-strains and cultured strains were downloaded from SILVA release
266 128[32], and SATIVA[33] was used to remove mislabeled strains. For *cpn60*, sequences were

267 downloaded from the cpnDB[34] as of 2016-10-21. The complete nucleotide sequences of group I
268 chaperonins, i.e. *cpn60* (also known as *hsp60* or *groEL*), which is found in bacteria, some archaea,
269 mitochondria and plastids, were used for building the database. Two datasets were downloaded,
270 both the FASTA file of all group I sequences and a reduced file with only reference genome
271 representatives. Taxonomic classifications were transferred from the SILVA annotation of
272 release 111 and then manually curated. Finally, for ATP9-NAD9, we used a database assembled
273 from curated sequences including 140 different *Phytophthora* species/hybrids (GenBank accession
274 numbers JF771616.1 to JF772053.1 and JQ439009.1 to JQ439486.1, and Bilodeau and
275 Robideau[35]; n.b. a total of 123 species are currently described; http://www.phytophthoradb.org).

276 When sequence and taxonomic data had been obtained for each of these genetic markers, we ran
277 the metaxa2_dbb software on each data set using the conserved, divergent and hybrid modes. We
278 also enabled the self-evaluation option, which performs a cross-validation of the database
279 performance similar to that of Richardson et al.[16]. For the self-evaluation we used the default
280 settings, which correspond to rebuilding the database ten times, each time using 90% of the input
281 sequences to build the database (the training set) and then subsequently classifying the remaining
282 10% of input sequences (the testing set) using Metaxa2. The predicted taxonomic classifications
283 were then compared against the taxonomic identity of each test sequence dervied from the
284 source databases at every taxonomic level, generating measures for sensitivity (proportion of test
285 sequences identified as matching the barcoding region), specificity (proportion of correctly
286 classified sequences at the taxonomic level in question), and the error per classification ratio
287 (proportion of incorrectly classified sequences per total classifications made).

288 In addition to the software self-evaluation, we also tested the classification performance of the
289 different databases on sequence fragments derived from the sequences used to build the
290 respective database. This evaluation followed the method used for the original Metaxa2 paper[17],
291 although we only generated fragments of a single length, viz. 150 nucleotides. The test sets were
292 generated by randomly selecting a stretch of 150 nucleotides from every sequence in the input
293 data for each barcoding region. We then used Metaxa2 version 2.2 to classify these simulated
294 read data sets and calculated the performance for each barcoding region in terms of accuracy
295 (proportion of correctly classified sequence fragments), misclassifications (incorrect assignments),
296 sensitivity (proportion of non-detected sequence fragments), and over-prediction (incorrect
297 assignment to a rank for which there is no reference belonging to the query taxa present in the
298 database). Sequence fragments were regarded as correctly classified if their reported taxonomy
299 corresponded to the known taxonomy of the input sequence that the fragment was derived from,
300 at every taxonomic level as reported by Metaxa2. If any incorrect taxonomic affiliations were
301 reported at any taxonomic level, the fragment was regarded as misclassified.

302 We finally compared the performance of the hand-curated Metaxa2 SSU rRNA database that is
303 bundled with the software to SSU rRNA databases built by metaxa2_dbb from the sequences in
304 SILVA release 111 and 128[28]. The native Metaxa2 database is based on SILVA release 111, which
305 means that the comparison between the native database and release 111 is relevant to understand
306 the differences between the manual and automatic database constructions. The difference to
307 release 128, on the other hand, is rather a test of whether the accuracy changes with the addition
308 of more reference sequences. The SILVA databases were created by downloading the FASTA file
309 representing the reference SSU sequences with 99% non-redundancy (SSURef_Nr99) with

310 taxonomy from SILVA. We then added the SSU sequences for the 12S rRNA used in the native
311 Metaxa2 database from MitoZoa[17,36]. From these, we used Metaxa2 version 2.1.2 (default settings)
312 to divide the SSU sequences by taxonomic domain. The resulting files were used as input for
313 metaxa2_dbb, which was run by retaining the HMM profiles from the native database, i.e. only
314 rebuilding the classification database. In all cases, taxonomy correction was used, and cutoffs
315 were manually set to "0,60,70,75,85,90,97"[17]. The full options were: "metaxa2_dbb -o
316 SSU_SILVAXXX -g SSU -p metaxa2_db/SSU/HMMs/ -t
317 SILVA_XXX_SSURef_Nr99_tax_silva.fasta -a archaea.fasta -b bacteria.fasta -c chloroplast.fasta
318 -e eukaryota.fasta -m mitochondria.fasta -n mitozoa_SSU.fasta --correct_taxonomy T --cutoffs
319 '0,60,70,75,85,90,97' --cpu 16". For each SILVA release, two databases were built, one with the
320 command above, and one in which filtering of taxonomic information was applied, adding the "--
321 filter_uncultured T --filter_level 6" options.

322 After these new SILVA-based classification databases had been constructed, we classified the
323 simulated SSU read fragments with high-quality taxonomic information used in the original
324 Metaxa2 evaluation, and ran this in the same way as in the original paper[17]. The results of the
325 classifications were investigated manually to make sure that errors made by Metaxa2 were due to
326 actual classification errors and not renaming of taxa, inconsistencies in taxonomy between
327 database versions, synonymous names used for one taxon, or misspellings. As in the original
328 Metaxa2 paper, a sequence fragment was regarded correctly classified if the reported taxonomy
329 corresponded to the known taxonomy of the input sequence at every taxonomic level, as
330 reported by Metaxa2. If the Metaxa2 classification was found to completely correspond to the
331 known taxonomic affiliation at all investigated taxonomic levels, the sequence fragment was

332 regarded as perfectly classified. If Metaxa2 reported any incorrect taxonomic affiliation at any
333 taxonomic level the fragment was regarded as misclassified.

334

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342 Author contributions

343 JBP and RTR conceived and designed the study. JBP designed the software, with input from
344 RTR, RMJ, MH and RHN. JBP implemented the software. JBP, KME and RHN updated the
345 software manual. RTR, CW, EDT, MM, KT, GJB and RMJ provided and curated data for
346 software evaluation. JBP, RTR, CW, MM, KT and KK evaluated software performance. JBP,
347 KME, MH and RHN updated the classification databases. JBP drafted the manuscript, with help
348 from RTR and RHN. All authors contributed to and approved the final manuscript.

349 Competing financial interests

350 The authors declare no competing financial interests.

351 ## Figure legends

352 **Fig. 1.** Self-evaluated performance of the Metaxa2 Database Builder in different operating modes
353 (conserved, divergent and hybrid) on ten different DNA barcoding regions. A) Proportion of
354 assigned sequences classified to the correct order (circles), family (diamonds) and genera
355 (triangles). B) Proportion of correctly assigned sequences multiplied with the proportion of
356 sequences included in the final classification databases (see Supplementary Fig. 2). The ATP9-
357 NAD9 genetic marker is not shown, because it only had relevant taxonomic differences at the
358 species level.

359

360 **Fig. 2.** Family level Metaxa2 performance on randomly generated 150 bp fragments originating
361 from the sequence datasets used to build the respective databases in the three different modes
362 (Conserved, Divergent and Hybrid). A) Proportions of fragments assigned to the correct
363 taxonomic family. B) Proportions of fragments assigned to an incorrect family. C) Proportions of
364 fragments not assigned, or not recognized as belonging to the investigated barcoding region, at
365 the family level. D) Family-level overpredictions, i.e. the proportions of sequence fragments
366 belonging to a family not present in the final database, which were still assigned to a (different)
367 family by Metaxa2. Note that the ATP9-NAD9 dataset is only used for species identification and
368 thus this marker would be expected to show perfect performance on the family level. Note also
369 that the Y-axis scales are different for B and for D compared to A and B.

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