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1 **Evaluating multiplexed next-generation sequencing as a method in palynology**  
2 **for mixed pollen samples**

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22 Short title: Evaluating NGS-based palynology

23 **Abstract**

24 The identification of pollen plays an important role in ecology, palaeo-climatology,  
25 honey quality control and other areas. Currently, expert knowledge and reference  
26 collections are essential to identify pollen origin through light microscopy. Pollen  
27 identification through molecular sequencing and DNA barcoding has been proposed  
28 as an alternative approach, but the assessment of mixed pollen samples originating  
29 from multiple plant species is still a tedious and error-prone task. Next-generation  
30 sequencing has been proposed to avoid this hindrance. In this study we assessed  
31 mixed pollen probes through next-generation sequencing of amplicons from the  
32 highly variable species-specific internal transcribed spacer 2 region of the nuclear  
33 ribosomal DNA. Further, we developed a bioinformatical workflow to analyse these  
34 high-throughput data with a newly created reference database. To evaluate the  
35 feasibility, we compared results from classical identification based on light  
36 microscopy from the same samples with our sequencing results. We assessed in  
37 total 16 mixed pollen samples, 14 originated from honey bee colonies and two from  
38 solitary bee nests. The sequencing technique resulted in higher taxon richness  
39 (deeper assignments and more identified taxa) compared to light microscopy.  
40 Abundance estimations from sequencing data were significantly correlated with  
41 counted abundances through light microscopy. Simulation analyses of taxon  
42 specificity and sensitivity indicate that 96% of taxa present in the database are  
43 correctly identifiable at the genus level and 70% at the species level. Next-  
44 generation sequencing thus presents a useful and efficient workflow to identify  
45 pollen at the genus and species level without requiring specialized palynological  
46 expert knowledge.

47

48

## 49 **Introduction**

50 Palynology, the scientific study of pollen and identification of its origin, plays an  
51 important role in studying mechanisms of plant-pollinator interactions (Wilcock  
52 and Neiland, 2002), resource use of flower-visiting animals (Kleijn and Raemakers,  
53 2008; Wcislo and Cane, 1996) and climate-related variation of plant communities  
54 through time (Marchant et al., 2001; Sugita, 1994; Tzedakis, 1993). Pollen grains  
55 often display a species-specific morphology with diverse structure and sculpture.  
56 However, it remains difficult to delineate between closely related species when  
57 using light microscopy (Mullins and Emberlin, 1997). As a result, many pollen types  
58 are simply grouped at genus or family level (Davies and Fall, 2001) and data  
59 analyses on pollen diversity are strongly limited (Bagella et al., 2013). DNA  
60 barcoding, i.e. to identify and classify organisms according to a nucleotide sequence  
61 was often and successfully applied to all major groups of organisms, also plants  
62 including pollen (Chen et al., 2010; Hebert et al., 2003; Zhou et al., 2007).  
63 Accordingly, molecular tools to analyze pollens have also substantially increased in  
64 their application and show great potential especially with difficult, also fossil taxa  
65 and those with low taxonomic knowledge (Bennett and Parducci, 2006; Wilson et  
66 al., 2010; Zhou et al., 2007).

67

68 It is further a promising new approach in ecology to directly determine the diversity  
69 of organisms in environmental samples (Sheffield et al., 2009; Valentini et al., 2009),  
70 i.e. samples that represent a mixture of species, e.g. faeces, soil or pollen collections,  
71 for which identification with classical methods is difficult or incomplete (Wilson et  
72 al., 2010). To analyze mixed sets of pollens originating from different plant  
73 organisms with DNA barcoding however is still a tedious and error-prone task,  
74 requiring manual separation of pollens to taxa, each to be amplified and sequenced  
75 individually. Studies evaluating applicability of high-throughput techniques to  
76 pollen materials are currently lacking (Taylor and Harris, 2012; Wilson et al., 2010)  
77 or are restricted to specific investigations using quantitative real time polymerase  
78 chain reaction (qRT-PCR) where prior information about present organisms is

79 required (Agodi et al., 2006; Schnell et al., 2010). Palynology would therefore benefit  
80 from species-level determination from mixed samples, larger counts, higher  
81 processing speed, improved objectivity, and automation to be attractive for large  
82 scale studies (Stillman and Flenley, 1996). Molecular methods based on high-  
83 throughput DNA-sequencing could provide the requested features to extent and  
84 improve classical pollen determination. Valentini et al. (2010) proposed next-  
85 generation sequencing (NGS) as a suitable method for this task. We agree with this  
86 idea and thus evaluated in this study the performance and reliability of the new  
87 sequencing and bioinformatical strategies by directly comparing it with data  
88 obtained by light microscopy.

89

90 Specifically we address the following challenges that emerge in DNA barcoding with  
91 mixed pollen samples. (1) A laboratory routine has to be defined which can be  
92 applied to all major plant clades, requiring universality of amplification priming  
93 regions and adequate length to be suitable for next-generation sequencing while  
94 holding enough sequence variation to differ between species. This routine includes  
95 DNA extraction, amplification, sample multiplexing, library preparation, sequencing  
96 with high-throughput devices and raw-data cleanup. Also, (2) a mapping algorithm  
97 has to be developed which adequately maps obtained sequences in their full length  
98 to references, preferably in a hierarchical progression with confidence values for  
99 each level of taxonomy. Further, this algorithm has to be with good performance to  
100 be able to process high-throughput data on a standard desktop computer and  
101 produce results in reasonable time. (3) A comprehensive reference database is  
102 required to derive the desired taxonomic annotations.

103

104 Several genetic marker regions have been proposed for DNA barcoding in plants  
105 that match the requirements, foremost presence and feasibility to be amplified in all  
106 investigated taxa, as well as low intra-specific but high inter-specific variability to  
107 succeed in being species-specific (Chen et al., 2010; Hebert et al., 2003;  
108 Hollingsworth et al., 2011; Zhou et al., 2007). In this study, we use the internal  
109 transcribed spacer 2 (ITS2) region, which has been shown to be suitable as a

110 barcode for plants (92.7% successful identifications in 6,600 samples, Chen et al.,  
111 2010; Buchheim et al., 2011). Also the enclosed genetic regions (5.8S and 28S) are  
112 highly conserved throughout the eukaryotes. Thus an universal primer for the  
113 analysis of probes consisting of multiple organisms is applicable with a low risk to  
114 exclude taxa from amplification (Chen et al., 2010; Keller et al., 2009; White et al.,  
115 1990). A further reason for choosing this marker is that a comprehensive ITS2  
116 database already exists (Koetschan et al., 2010) helping to prepare reference  
117 sequences suitable for our needs.

118

119 We approached the targeted tasks by combining and adapting existing molecular  
120 and bioinformatical tools to develop new functionalities for DNA barcoding of pollen  
121 samples that consist of multiple taxa. We then evaluated the performance and  
122 quality of the molecular and bioinformatical workflow by comparing our results  
123 with data from classical light microscopy identification of pollen samples. Further,  
124 we tested the applicability for samples with low pollen contents and performed  
125 computer-based simulations to validate that the bioinformatical classification  
126 pipeline is trustable.

## 127 **Materials and Methods**

### 128 **Pollen collection**

129 The honey-bee pollen samples were collected in twelve different landscapes in the  
130 region around Bayreuth, Germany. The distance between landscapes was at least 3  
131 km leading to diversified pollen inputs depending on the surrounding floral  
132 resources. In the centre of each landscape we established a honey bee colony (*Apis*  
133 *mellifera carnica* L.) with a pollen trap in front of the hive entrance. Returning  
134 foragers had to pass a 5 mm grid taking off the pollen loads from their hind legs.  
135 From 21.07.2009-12.08.2009 every one to three days accumulated pollen loads  
136 were removed from the traps and stored as individual samples at -18 °C until the  
137 end of the sampling period. Pollen samples were dried at 30 °C for one week.  
138 Further, to assess variability in resource use of honeybees at one location, samples  
139 from three colonies located at the same study site were separately analysed (in the

140 following designated as Samples 12a, 12b and 12c). From each of the fourteen  
141 samples (one per colony) 20% of the collected pollen were randomly taken and  
142 mixed for further analyses.

143

144 We performed NGS as well as microscopic assessment of the samples. The samples  
145 were split into independent aliquots for these separate, blinded analyses. NGS was  
146 performed by AK, GG and MA, whereas the samples were classified through classical  
147 light microscopy by ND with expert guidance by KvO, without knowledge of the  
148 other group's results.

149

150 Two further pollen samples were obtained from solitary bee nests (*Osmia bicornis*  
151 L.) in October 2012 by swabbing the cell walls with cotton buds (Keller et al., 2013).  
152 In contrast to the relatively pure pollen samples obtained from honey bees, this  
153 experiment reflects samples strongly contaminated with nest building materials  
154 (soil) and faeces, challenging to analyse with traditional methods. Solitary bee  
155 samples were thus only processed with NGS.

156

### 157 **Classical pollen identification**

158 Pollen samples were first analyzed using light microscopy in the LAVES Institut für  
159 Bienenkunde in Celle, Germany. For the microscopic pollen determination, 10mg  
160 pollen loads of each sample were homogenized in 50ml demineralized water with a  
161 magnetic stirrer for one hour. 15 µl of the solution and 30 µl demineralized water  
162 were transferred to a slide, distributed equally over an area of the size of a cover  
163 glass and embedded in glycerin gelatin after complete dehydration following the  
164 method of Behm et al. (1996). From each sample 500 randomly selected pollen  
165 grains were determined on genus level and where possible to species level. Very  
166 rarely occurring pollen types were not determined (Behm et al., 1996).

167

### 168 **Molecular pollen identification**

169 Second pollen identification was done by DNA barcoding of the ITS2 region. The  
170 main working steps described below were DNA extraction, amplification,  
171 sequencing, bioinformatic cleanup and taxonomic classification.

172

173 DNA extraction, amplification and sequencing: For each sample, 2 g of pollens were  
174 added to 4 ml of bidest H<sub>2</sub>O and homogenized with an electronic pistil within a  
175 plastic tube. Of this emulsion, 200 µl (equaling approximately 50 mg of pollens)  
176 were taken for the following extraction. We grinded the aliquot with the TissueLyser  
177 LT (Qiagen, Hilden, Germany) and extracted DNA using the Machery-Nagel (Düren,  
178 Germany) NucleoSpin Food Kit. We followed the special supplementary guidelines  
179 for pollen samples provided by the manufacturer. For polymerase chain reaction  
180 (PCR) amplification we used the primers S2F and ITS4R originally designed by Chen  
181 et al. (2010) and White et al. (1990) to span a mean region of approximately 350bp.  
182 This covers the complete ITS2 region. We adapted those primers to match 454  
183 sequencing purposes and multiplexing by adding the 454 specific Adapters A and B,  
184 the linker key, and a variable multiplex identifier (MID). Thus the forward “fusion”  
185 primer was 5'-CGT ATC GCC TCC CTC GCG CCA TCA GAT GCG ATA CTT GGT GTG AAT  
186 -3' and the reverse “fusion” primer 5'-5'CTA TGC GCC TTG CCA GCC CGC TCA GXX  
187 XXX XXX XXT CCT CCG CTT ATT GAT ATG C-3', where the X-region designates a  
188 variable MID. In total, 16 MIDs were taken from the official Roche technical bulletin  
189 (454 Sequencing Technical Bulletin No. 005-2009, April 2009) to be able to process  
190 all our samples with one sequencing chip.

191

192 PCR reaction mixes consisted of 0.25 µl of each forward and reverse primer (each  
193 30µM molar), 3 µl of template DNA and 25µl of Phusion High-Fidelity DNA  
194 polymerase PCR 2x MasterMix (Thermo Scientific, Waltham, MA, USA). Bidest H<sub>2</sub>O  
195 was added to a reaction volume of 50 µl. Samples were initially denaturated at 94 °C  
196 for 4 min, then amplified by using 37 cycles of 95 °C for 40 s, 49 °C for 40 s and 72 °C  
197 for 40 s. A final extension (72 °C) of 5 min was added at the end of the program to  
198 ensure complete amplification. All samples were amplified in ten separate aliquots  
199 to reduce random effects on the community during PCR amplification (Fierer et al.,



200 2008). PCR amplicons of these ten replicates were combined, gel-electrophoresed,  
201 trimmed for amplicon length and cleaned with the HiYield PCR Clean-up Kit (Real  
202 Biotech Corporation, Banqiao City, Taiwan) according to the manufacturers  
203 description. Cleaned samples were quantified using a Qubit II Flurometer  
204 (Invitrogen/Life Technologies, Carlsbad, CA, USA) and the dsDNA High-Sensitivity  
205 Assay Kit (also Invitrogen/Life Technologies) as described in the vendors protocol.  
206 We used the BioAnalyzer 2200 (Agilent, Santa Clara, CA, USA) with High Sensitivity  
207 DNA Chips (also Agilent) for verification of fragment length distributions.  
208 Pyrosequencing and library preparation was performed according to the guidelines  
209 for the GS junior (Roche, Basel, Switzerland). Sequencing was performed in-house  
210 with a GS junior device located in the Department of Human Genetics (University of  
211 Würzburg, Germany) with original Roche GS junior titanium chemistry.

212

213 Bioinformatic cleanup: Data was demultiplexed into the different samples using the  
214 MID adapter sequences and the QIIME software (Caporaso et al., 2010; Kuczynski et  
215 al., 2011). During this step, only sequences spanning both priming regions were  
216 further used, i.e. only completely sequenced amplicons. Primers, adapters and MIDs  
217 were trimmed. Chimeric checking and quality filtering was also performed during  
218 this step. We restricted data to high quality reads with a phred score  $\geq 27$ , (Kunin et  
219 al., 2010) and no reads with ambiguous characters were included in the following  
220 downstream analyses.

221

222 Hierarchic classification: Taxonomic assignments were performed with the RDP  
223 (Ribosomal Database Project) classifier (Wang et al., 2007) and an ITS2 specific,  
224 novel reference set created and evaluated as described below. Further, we applied a  
225 bootstrap cut-off at 85% as classification threshold with respect to the maximum f-  
226 measure in the training database evaluation (also see below).

227

### 228 **Method comparison statistics**

229 Most of the analyses were performed on a generic level, as both methods yielded  
230 some taxa only assignable to this level. With a generic analysis all identified taxa

231 were directly comparable. With this data we compared taxon richness and identified  
232 species overlaps and differences obtained from the two methods. Rarefaction curves  
233 for each plot were generated with R (R Development Core Team, 2010) in the NGS  
234 data to evaluate species richness in relation to sequencing depth. Abundance was  
235 assessed relatively in percent of total number of reads and in percent of 500 pollen  
236 grains (Behm et al., 1996) for NGS and light microscopy, respectively. We used  
237 overall and per-plot abundance of these relative accounts to compare between the  
238 two methodologies by Pearson's product moment correlation using R (R  
239 Development Core Team, 2010).

240

### 241 **Molecular reference database training**

242 Taxonomic classifications with DNA barcodes are currently mostly done via  
243 phylogenetic analyses (Buchheim et al., 2011), pairwise alignments with specific  
244 reference sequences (Chen et al., 2010) or BLAST searches (Basic Local Alignment  
245 Search Tool) (Altschul et al., 1990) in GenBank (Benson et al., 2010) or other  
246 nucleotide databases. The first both methods require that prior knowledge about  
247 taxonomy is present to select suitable taxa included into the recalculated  
248 phylogenetic tree or alignment. This is not feasible for mixed pollen collections,  
249 where the included taxa are unknown prior to assessment or stem from very  
250 different taxonomic groups. BLAST searches have to be performed very carefully, as  
251 hits may include local alignments and identity calculations may thus be based only  
252 on parts of the query and reference sequences. Further, the raw output of a BLAST  
253 search is often obscured as a lot of hits are not taxonomically annotated or flagged  
254 as "environmental samples". A novel approach to tackle these drawbacks has been  
255 proposed with a Bayesian classification algorithm (Wang et al., 2007). It provides  
256 hierarchical taxonomic assignments of DNA sequences and is well accepted in the  
257 scientific community as especially high throughput analyses profit from the  
258 efficiency and accuracy of the algorithm (Caporaso et al., 2010). Currently, the only  
259 publicly available training sets are limited to bacterial 16S (Wang et al., 2007) and  
260 fungal large ribosomal subunit (Liu et al., 2012).

261

262 In this study, a new ITS2 training set was designed for plants. We used the ITS2-  
263 Database as an original database which is restricted to structure-validated  
264 sequences (Koetschan et al., 2010). All ITS2 sequences matching the taxonomic  
265 group “Viridiplantae” and with a sequence length between 200 bp and 400 bp were  
266 downloaded, resulting in 73,853 sequences (accessed 3<sup>rd</sup> March 2013). The  
267 taxonomy for each sequence was assigned using the GI (GenBank Identifier) and the  
268 corresponding NCBI taxonomy (Federhen, 2012) by Perl scripting and reformatted  
269 to be usable with the python script “assign taxonomy.py” of the QIIME (Caporaso et  
270 al., 2010) package. Additionally, RDP required formats of these preprocessed files  
271 were generated. Training was performed with the RDP classifier v2.2 (Wang et al.,  
272 2007) as implemented in QIIME. Before training of the final set, we evaluated the  
273 performance by varying several parameters of the underlying data to maximize  
274 effectiveness and allow quality estimations of the assignments as described in the  
275 following.

276

277 Pre-clustering evaluation: Due to intraspecific variation (Song et al., 2012) and  
278 sequencing errors in the underlying data (Kunin et al., 2010), pre-clustering of  
279 reference sequences prior to training may prove useful to increase reliability of the  
280 results (Lan et al., 2012). Thus, from the full data-set we generated eleven separate  
281 training sets differing in the pre-clustering threshold of sequences before the actual  
282 training. Clusters of sequences were generated at identity levels of 90%, 91% ...  
283 100%, and only the most abundant sequence of each cluster was picked. This also  
284 generated an even distribution of taxonomic units in the sets. To assess the  
285 assignment quality and depth, each sequence was reclassified to the training set.  
286 Then starting from the root of the taxonomy of each sequence, every taxonomic  
287 level of the assignment was compared to the correct taxonomy. If the bootstrap of  
288 an assignment was less than 0.8, the level (and all sub-levels) was considered as  
289 unassignable. If there was a mismatch between assigned taxonomy and expected  
290 taxonomy, the number of remaining sub-levels (plus one), was called erroneous  
291 levels. The number of assigned levels before the first mismatch or unassignable level  
292 was called correct levels.

293

294 Cut-off and assignment quality evaluation: To estimate assignment qualities, the test  
295 and training data had to be distinct sets. Further, we wanted to evaluate the  
296 effectiveness to identify “new species” that do not have representatives in the  
297 training data (Lan et al., 2012). The complete ITS2 reference data set was thus for  
298 testing purposes artificially split into three sets representing “training data”, “test  
299 data A” with references, and “test data B” without references. This was achieved by  
300 the following procedure: species with multiple sequences were separated into “test  
301 data A” (one sequence) as well as “training data” (remaining sequences). Species  
302 with only a single deposited sequence were assigned to category “test data B”. For  
303 this evaluation purpose, the algorithm was trained only with the set “training data”  
304 (36,418 sequences). According to the measures for the RDP classifier evaluation  
305 performed by Lan et al. (2012) for the original 16S dataset we estimated the number  
306 of “true positive” (TP) and “false negative” (FN) assignments by classifying  
307 sequences of “test data A” (10,635 sequences), where references were present in the  
308 “training data”, Only correct assignments were considered as TP, whereas wrong  
309 assignments (to a different species) were added to the list of FNs. Similarly, we  
310 classified sequences of “test data B” (26,800 sequences) to determine the number of  
311 “true negative” (TN) and “false positive”(FP) hits. With that, we calculated  
312 sensitivity  $SN = \frac{TP}{TP+FN}$  to identify existing taxa and specificity  $SP = \frac{TN}{TN+FP}$  to leave  
313 sequences without references unclassified. Using these split data-sets, we were able  
314 to estimate SN at species and genus level, whereas SP was only assessable at the  
315 species level. We optimized our assignment bootstrap value for classification by  
316 maximizing the f-measure as the harmonic mean of sensitivity and specificity at  
317 species level =  $\frac{2*SN*SP}{SN+SP}$ .

318

## 319 **Results**

### 320 **Pollen high-throughput sequencing and classification**

321 In total, our study produced 14,924 raw sequences for pollen samples passing  
322 Roche's quality filtering of the 454 junior sequencing device. Of these, 9,310 ITS2  
323 sequences matched our extended quality standards. The remainders were dismissed  
324 as too short (<200 bp), with low quality score (<27), excessive homopolymers (>5  
325 bp), chimeric or mismatches in primer regions (Caporaso et al., 2010; Kunin et al.,  
326 2010). After removal of adapters and primers, mean sequence length was 348,3 bp  
327 ( $\pm$  28 bp standard deviation), spanning the complete ITS2 region. Individual  
328 samples comprised 219-1,179 reads, with mean read length of 330,5 bp – 363,9 bp  
329 ( $\pm$  3,8 bp – 68,2 bp standard deviation). Beside plant sequences, we also found  
330 several fungal sequences, belonging to *Issatchenkia occidentalis*, *Cochliobolus sativus*,  
331 *Phoma* sp. and *Lewia infectoria*, which are regularly inhabiting or infecting plant  
332 tissues.

333

#### 334 **Honey bee pollen samples**

335 For the samples collected by honey-bees, 98.9% of all reads were assignable to  
336 genus level with a bootstrap confidence higher or equal than 0.85. At the species  
337 level we were able to classify 61.6% of our reads using the same bootstrap cut-off.  
338 Reducing the filter's required sequence length to 150 bp did not produce any new  
339 classifiable plant taxa. Taxon richness was not correlated with the number of reads  
340 within a sample (Pearson's correlation,  $r = -0.099$ ,  $df = 12$ ,  $t = -0.3453$ ,  $p\text{-value} >$   
341  $0.05$ ). Rarefaction showed that we reached a plateau regarding genera richness in all  
342 samples (Fig. 1A). These observations suggest that the sequencing depth was  
343 adequate to assess the underlying taxon richness.

344

345 We identified a total of 29 different genera of 16 families when we combined the  
346 results from molecular sequencing and microscopy (Tab. 1). Further, 24 taxa were  
347 also identifiable at the species level. With NGS we found 13 genera that were not  
348 identified through microscopy, whereas four genera (*Heracleum*, *Carduus*, *Phacelia*,  
349 *Convolvulus*) that were identified by light microscopy were missing in the NGS  
350 results although having references in the database. One genus (*Vitis*) had no

351 trustable reference sequence in the database and was thus also not identifiable with  
352 the NGS method.

353

354 From the phenology of the pollens and presence at plots, we assume that a  
355 misidentification of very similar pollens happened with light microscopy which was  
356 revealed by NGS: *Tanacetum* and *Scorzoneroides* were both manually misclassified  
357 as *Taraxacum*. We observed higher intra-generic taxon richness for *Trifolium*,  
358 *Hypochaeris*, *Chamerion* through NGS, yet lesser in *Centaurea* (Fig. 1B).

359 Improvement of the taxonomic assignment was found in four genera, where species  
360 levels were obtainable only through NGS. However, *Helianthus* was only classified at  
361 genus level, whereas microscopy was able to identify it as *Helianthus annuus*.

362

363 Based on NGS data, taxon richness within the samples ranged from 4 to 12 taxa that  
364 were at least classifiable at genus level (Fig. 1B). Correspondingly, diversity ranged  
365 from 4 to 12 taxa for the microscopy assessment. Pollen diversity collected by the  
366 three colonies from site twelve was 12, 10 and 12 taxa, respectively. The  
367 compositional profile was similar for the dominant pollen taxa in all three samples,  
368 but still showed considerable variation (Fig. 1B).

369

370 Over all samples, we found a strong correlation of abundance estimations between  
371 the two identification methods (Pearson's correlation,  $r = 0.86$ ,  $t = 8.71$ ,  $df = 26$ ,  $p <$   
372  $0.001^{***}$ , Fig. 2). This relationship is also reflected on a per plot basis, yet with lower  
373 correlation coefficient (Pearson's correlation,  $r = 0.66$ ,  $t = 17.36$ ,  $df = 390$ ,  $p <$   
374  $0.001^{***}$ ). These results indicate that the abundance estimates of taxa within plots  
375 show relatively high similarity between the two methods.

376

### 377 **Pollens in solitary bee nests**

378 Pollen samples from both solitary bee nests were successfully processed with 100%  
379 of reads identifiable at genus level despite high contamination of the samples with  
380 nesting materials and faeces. Both samples harbored *Brassica* sp. and *Dioscorea* sp.

381 pollens, the latter most likely *Dioscorea (Tamus) communis* as the only  
382 representative of the Dioscoreaceae present in the sampling region.

383

#### 384 **Molecular reference database training**

385 Pre-clustering of data prior to training of the RDP classifier did not improve the  
386 overall performance of classifications (Fig. 3). This was the case both for depth of  
387 the assignment as well as the mean number of incorrectly assigned levels, which  
388 respectively increase and decrease with higher pre-clustering thresholds. We thus  
389 used a cut-off at 100% sequence identity, which equals unique sequences, for the  
390 final training set. With that, of the 73,853 tested database sequences, 55,028 were  
391 positively identifiable at the species and further 10,518 at the genus level.

392 Surprisingly, 6,104 sequences were assignable only to phylum level. They likely  
393 represent contaminations in the reference database.

394

395 Regarding determination of the optimal cut-off threshold, specificity and sensitivity  
396 of the novel/known classifications are shown with their dependency of the  
397 bootstrap in Fig. 4. The best classification by means of f-measure is achieved with a  
398 bootstrap cutoff of 0.85. Specificity and sensitivity at this threshold for species level  
399 were both approximately 70%. At the genus level, sensitivity to correctly identify a  
400 genus increased to 96%. We thus recommend this threshold when using the RDP  
401 classifier with the generated training data.

402

403 Currently, all sequences in the reference data-set accumulate to 37,435 different  
404 plant species and 6,162 genera according to NCBI taxonomy (Federhen, 2012). The  
405 complete reference dataset is available for download and public usage at  
406 <http://www.dna-analytics.biozentrum.uni-wuerzburg.de>.

#### 407 **Discussion**

408 The demand for methods to identify pollen samples at a high-throughput level is  
409 increasing for many applications in ecology and paleo-climatology (Bennett and  
410 Parducci, 2006; Sheffield et al., 2009; Taylor and Harris, 2012; Valentini et al., 2009;

411 Wilson et al., 2010; Zhou et al., 2007). DNA barcoding is a frequently and  
412 successfully applied method, yet pollens of mixed samples originating from more  
413 than one source are currently not assessable through standard methods. Valentini et  
414 al. (2010) proposed that next-generation sequencing may counter this deficiency,  
415 i.e. to investigate such mixed samples by identifying all included plant organisms  
416 together without manual separation. The goals of this study were thus to develop,  
417 and moreover evaluate, a molecular laboratory procedure and bioinformatical  
418 analysis for such a task. The complete workflow was applied to pollen samples from  
419 two different studies (in total 16 samples). The resulting gene sequences allowed to  
420 successfully identify taxon richness and abundance of the underlying samples. The  
421 resulting taxonomic resolution is similar or better than results from classical light  
422 microscopy. Details of the performance of each individual step of the workflow and  
423 the resulting methodological and biological relevance are discussed in the following.

424

#### 425 **High-throughput pollen sequencing**

426 In general, our laboratory workflow was suitable in processing mixed pollen probes  
427 through next-generation sequencing. However, quality filtering according to our  
428 rigorous restrictions reduced the obtained sequences from approximately 15,000  
429 sequences to 10,000. Most of them were removed due to failure to include both  
430 primer regions and/or multiplex identifier due to low quality scores towards the  
431 end of sequences or short read lengths (Caporaso et al., 2010). The first indicates  
432 that a large proportion of reads was not fully sequenced with sufficient quality,  
433 whereas the latter shows that the primers also amplified shorter fragments than the  
434 intended plant ITS2 region. Not fully sequenced reads are a technical issue that is  
435 regularly improved by increase of read length and quality through new generations  
436 of sequencing devices and chemistry (Metzker, 2009). Improvements are also  
437 expectable by applying paired-end strategies, as quality near the ends will increase,  
438 or to use technologies with general lower sequencing error rates. Shorter, fully  
439 sequenced sequences are project specific problems, but also expectable: as a  
440 drawback of universal primers, they will as well amplify fungal ITS2 (White et al.,  
441 1990) ranging from ~100 to 250 bp and even other eukaryotic protists with far



442 shorter ITS2 regions (Keller et al., 2009). Further, the existence of non-functional  
443 pseudo-genes is known (Harpke and Peterson, 2008). Thus studies investigating  
444 plant ITS2 sequences should account for a sufficient overhead of estimated  
445 sequences per sample during project design due to sequencing technology and  
446 potential contamination through unwanted organisms (Parameswaran et al., 2007).  
447 The remaining high quality reads showed a high proportion of classifiable  
448 sequences (~99%), whereas reduction of the minimum sequence length had no  
449 impact on plant species diversity. Both observations suggest that the filters are  
450 adequate to concentrate on the data of interest, i.e. plant sequences.

451

### 452 **Classification pipeline**

453 To be able to use the RDP classifier (Wang et al., 2007) for taxonomic assignments  
454 with plants and with the ITS2 marker, we re-trained the algorithm with structurally  
455 verified sequences obtained from the ITS2 database (Koetschan et al., 2010). The  
456 underlying dataset incorporates more than 70,000 different plant sequences and  
457 represents a cross-section throughout the Viridiplantae. Sequences originate from  
458 all biogeographic regions of the world since the primary database is GenBank  
459 (Benson et al., 2010). Currently, all sequences in the reference data-set accumulate  
460 to 37,435 different plant species and 6,162 genera according to NCBI taxonomy  
461 (Federhen, 2012). Exemplarily for the data analysed in this study, the dataset covers  
462 79% of all vascular plant genera and 54% of species known to exist within the  
463 Federal state Bavaria, Germany, where our samples were obtained (comprehensive  
464 plant database <http://www.bayernflora.de>, accessed 6th November 2013,  
465 Staatliche Naturwissenschaftliche Sammlungen Bayern, 2013). As 99% of reads  
466 were classifiable to genus level and only one genus (*Vitis*) of the assessed 29 genera  
467 in total was missing in the reference database, most of abundant and bee relevant  
468 plant genera seem to be included. Further, the classifier's dataset is updateable to  
469 match the constantly increasing numbers of sequences deposited in GenBank and  
470 the ITS2 database in the future (Wang et al., 2007).

471

472 In the computational evaluation of database and classifier for an ITS2 dataset, we  
473 obtained values comparable to those of existing datasets published for bacteria  
474 (Wang et al., 2007) and fungi (Liu et al., 2012). Taxonomic classifications performed  
475 best regarding sensitivity, i.e. to identify taxa existing in the database, and  
476 specificity, i.e. to restrain from classifying organisms without references, at a  
477 bootstrap threshold level of approximately 0.85 (Lan et al., 2012). Species and genus  
478 level sensitivity to correctly identify sequences with this bootstrap were 70% and  
479 96%, respectively. This is similar to the classifier's preferred level used to classify  
480 microbial organisms (0.80, Lan et al., 2012; Wang et al., 2007). From a technical  
481 perspective it is thus valid to apply the classification algorithm also for ITS2  
482 sequences of plants.

483

#### 484 **Comparison of assessment methods**

485 Using next-generation sequencing, we were clearly able to improve palynology  
486 diversity assessments in comparison with traditional optical microscopy. This  
487 appears in novel taxa that were identified, as well as improvement of classification  
488 of taxa and better possibilities to distinguish species within a genus. Further, some  
489 misidentifications of pollen through microscopy were revealed that were caused by  
490 very similar morphological appearance of closely related species. Also, molecular  
491 assessments were successful for solitary bee nest samples, where swabs included  
492 pollens as well as contaminating materials. Sequencing assessments were  
493 repeatable, identifying similar diversity in samples obtained from different bee  
494 colonies placed within the same landscape.

495

496 However, using the high-throughput approach we also encountered limitations,  
497 which are partly related to the data used for training of the classifier. Regarding the  
498 Vitaceae, the ITS2 database is currently lacking trustable reference sequences. We  
499 validated the only existing sequence, which was considerably short (~200 bp) and  
500 derived from a whole genome shotgun sequencing study (assembled sequence from  
501 short length reads, GenBank ID: AM462492.2, Velasco et al., 2007). Due to intra-  
502 genomic variation of the ITS2 (Song et al., 2012), we assume the assembly yielded a

503 consensus, stacked ITS2 sequence, unusable for barcoding purposes or that a non-  
504 ITS2 region was falsely identified as such by the ITS2 database annotation algorithm  
505 (Keller et al., 2009). We therefore dismissed the sequence as missing within the  
506 reference database. In general, taxa missing or with inadequate sequences in the  
507 underlying database are not identifiable. As shown exemplarily for the geographic  
508 region Bavaria, 22% of known plant genera are missing and thus the current  
509 coverage is far from complete (Staatliche Naturwissenschaftliche Sammlungen  
510 Bayern, 2013). Also, valid sequences with wrong taxonomic annotations may lead to  
511 mis-training of the classification model regarding the respective taxa (Bridge et al.,  
512 2003). This is exemplified by a proportion of sequences re-classified in the  
513 evaluation to a different phylum, suggesting wrong taxonomic annotation of  
514 GenBank database sequences. To address limitations of the underlying database  
515 (missing or misclassified sequences) in a given research question, we suggest that  
516 applied studies should consider also reviewing one cross-section pool of all samples  
517 in parallel through optical means to verify the overall richness of taxa relevant for  
518 the study. This will also maintain comparability between studies applying  
519 traditional and molecular approaches. Despite these database-specific drawbacks,  
520 the classifier produced taxonomic assignments that are congruent with light  
521 microscopy, and thus corroborating the positive technical evaluation of the pipeline  
522 above with a direct comparison of biological data.

523

524 Abundance estimations of both methods showed a strong correlation, suggesting  
525 that abundance estimates based on high-throughput sequencing regarding high or  
526 low sequence frequency of taxa within the sample are valid. In our study, we took  
527 care to reduce amplification biases through PCR with ten aliquots of each sample  
528 simultaneously (typical in microbiota studies: three, Fierer et al., 2008) and a low  
529 number of amplification cycles (Suzuki and Giovannoni, 1996). Still, abundances  
530 retained from PCR amplified DNA samples have to be regarded critically, as  
531 amplification biases through priming preference of specific taxonomic groups,  
532 random effects and the exponential nature of the amplification process are not  
533 excludable (Spooner, 2009; Suzuki and Giovannoni, 1996). Abundances are thus

534 likely better interpreted categorical (e.g. high abundance, low abundance) than with  
535 linear association. With the advent of increased sequencing throughput and third-  
536 generation single molecule sequencers without need for amplification (Metzker,  
537 2009; Roberts et al., 2013), improved abundance estimations by sequencing are  
538 likely in the near future.

539

540 Expenses per sample were almost equal for both applied methods when considering  
541 time consumption and consumables. As the trend of sequencing technologies goes  
542 rapidly toward higher throughput and resulting multiplexing possibilities (Kozich et  
543 al., 2013; Metzker, 2009), we expect price efficiency per sample with next-  
544 generation sequencing to outpace optical assessments in the near future.

545

#### 546 **Fields of application**

547 Various applications arise for the proposed method. These include studies of pollen  
548 material from various origins, including plants themselves, pollinators, soil samples  
549 and wind collections. The results of such assessments are of great importance in  
550 identifying the diversity and specialization of plant-pollinator interaction networks  
551 (Bosch et al., 2009) and also in supporting agricultural and ecological management  
552 decisions (e.g. Girard et al., 2012; Odoux et al., 2012). Further, paleo-ecological and  
553 climate-change associated studies investigating fossil pollens may also largely profit  
554 (Bennett and Parducci, 2006).

555

556 Special attention is currently required in quality control of honey-bee products,  
557 including the geographical origin, correct labeling of different varieties based on the  
558 used floral resources and detection of contaminations from genetically modified  
559 (GM) crops (Hemmer, 1997; Picard-Nizou et al., 1995). As pollen is naturally  
560 incorporated into honey and protocols to isolate them are common usage  
561 (Sowunmi, 1976), high-throughput sequencing and classification may contribute  
562 largely to this endeavor by facilitating the analytical process and inclusion of  
563 references from plant taxa throughout the world (Ruoff et al., 2007; Sowunmi,  
564 1976).

565

566 Furthermore, the methodology may be equivalently applied to other questions not  
567 only related to pollens. Other target samples are naturally occurring communities of  
568 plants, (e.g. green algae), or artificially mixed probes of plant tissue fragments  
569 (Schlumbaum et al., 2008). As the primers used in this study also efficiently amplify  
570 fungal ITS2 sequences, ancillary information is automatically gained about this  
571 group including pathogens as *Ascosphaera* spp. that may be present in collected  
572 pollen samples and vectorised through harvesting flights of worker bees (Gilliam,  
573 1990; White et al., 1990).

## 574 **Conclusions**

575 Expert knowledge is essential to identify pollens adequately through traditional  
576 light microscopy and taxonomic expertise is also often restricted to specific plant  
577 groups or geographical regions. Further, mixed samples of pollens from several  
578 plant origins present a problem in current palynology. With this study we evaluated  
579 next-generation sequencing to approach pollen assessments through molecular  
580 techniques including their bioinformatical analysis. The analytical pipeline is  
581 designed for high-throughput data, but also adaptable to single sequences. It is a  
582 useful technique broadening the assessment capabilities from expert labs to all  
583 workgroups with access to standard molecular laboratory equipment. Further, our  
584 results show that this assessment method improves the standard technique with  
585 regard to taxonomical deepness, overall diversity and rectifying misidentifications.

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593 **Data Accessibility**

594 Sequences have been deposited at the ENA:SRA (<https://www.ebi.ac.uk/ena>) and  
595 are accessible under study accession number PRJEB5016. The used training set  
596 alongside installation and application notes is available for download at  
597 <http://www.dna-analytics.biozentrum.uni-wuerzburg.de>.

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768

769

770 **Tables**

771 Tab. 1: Plant families with their number of genera and number of species assessed  
772 by Next Generation Sequencing (NGS) and optical microscopy.

773 **Figures**

774 Figure 1: A) Rarefaction of genera richness obtained for each honey bee sample with  
775 respect to sequencing depth. B) Plot-based comparison of pollen identification  
776 through optical microscopy and NGS. Taxonomic assignments are illustrated at the  
777 genus level. Positive identification of a taxonomic unit within a sample is indicated  
778 in the community matrix as dark gray for microscopy and light gray for NGS.

779 Relative abundance estimations are indicated by size at two levels, i.e.  $\geq 5\%$  (fully-  
780 filled box) and  $< 5\%$  (half-filled box) of total abundance within a sample. Genera  
781 misidentified in optical microscopy were combined for direct comparison and are  
782 indicated by quote marks in abbreviated form (Tar = *Taraxacum*, Sco =  
783 *Scorzoneroides*, Tan = *Tanacetum*). Availability in the reference database is indicated  
784 in the column DB. \*For sample 12, three samples were taken from the same study  
785 site but different colonies. All three samples were analyzed using NGS to evaluate  
786 repeatability, yet optical microscopy was only performed for 12a.

787  
788 Figure 2: Overall log-scaled relative abundance comparison of genera between the  
789 two classification strategies. Rectangles at the axes represent genera only found  
790 with one of the two sampling techniques. Pearson's correlation  $r = 0.86$ ,  $t = 8.71$ ,  $df =$   
791  $26$ ,  $p < 0.001^{***}$ .

792  
793 Figure 3: Pre-clustering evaluation: Starting from the root of the taxonomy of each  
794 sequence, every taxonomic level of the assignment was compared to its correct  
795 lineage. The overall mean of correct assignments according to the different pre-  
796 clustering levels is presented as green dots in the figure (left scale). Similarly, each  
797 sequence was tested for erroneous levels of classification with means displayed as  
798 red squares and the scale on the right side.

799

800 Figure 4: Dependence of sensitivity and specificity by the bootstrap threshold.  
801 Sensitivity to identify at species level is illustrated with a red and single-dashed line,  
802 whereas generic identification as a red two-dashed line. Specificity is displayed as a  
803 green dotted line. The harmonic mean of both species level measures is displayed by  
804 a solid black curve, maximized at approximately 0.85 as the suggested optimal  
805 classification threshold.