

1 **Efficient assessment of nocturnal flying insect communities by**
2 **combining automatic light traps and DNA metabarcoding**

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17

18 **Summary**

- 19 1. Increasing evidence for global insect declines is prompting a renewed interest in the survey of
20 whole insect communities. DNA metabarcoding can contribute to assessing diverse insect
21 communities over a range of spatial and temporal scales, but efforts are still needed to optimise
22 and standardise procedures, from field sampling, through laboratory analysis, to bioinformatic
23 processing.
- 24 2. Here we describe and test a methodological pipeline for surveying nocturnal flying insects,
25 combining a customised automatic light trap and DNA metabarcoding. We optimised laboratory
26 procedures and then tested the methodological pipeline using 12 field samples collected in
27 northern Portugal in 2017. We focused on Lepidoptera to compare metabarcoding results with
28 those from morphological identification, using three types of bulks produced from each sample
29 (individuals, legs and the unsorted mixture).
- 30 3. The customised trap was highly efficient at collecting nocturnal flying insects, allowing a small
31 team to operate several traps per night, and a fast field processing of samples for subsequent
32 metabarcoding with low contamination risks. Morphological processing yielded 871 identifiable
33 individuals of 102 Lepidoptera species. Metabarcoding detected a total of 528 taxa, most of
34 which were Lepidoptera (31.1%), Diptera (26.1%) and Coleoptera (14.7%). There was a
35 reasonably high matching in community composition between morphology and metabarcoding
36 when considering the 'individuals' and 'legs' bulk samples, with few errors mostly associated
37 with morphological misidentification of small microlepidoptera. Regarding the 'mixture' bulk
38 sample, metabarcoding identified nearly four times more Lepidoptera species than
39 morphological examination.
- 40 4. Our study provides a methodological metabarcoding pipeline that can be used in standardised
41 surveys of nocturnal flying insects, showing that it can overcome limitations and potential
42 shortcomings of traditional methods based on morphological identification. Our approach
43 efficiently collects highly diverse taxonomic groups such as nocturnal Lepidoptera that are poorly
44 represented when using Malaise traps and other widely used field methods. To enhance the
45 potential of this pipeline in ecological studies, efforts are needed to test its effectiveness and
46 potential biases across habitat types and to extend the DNA barcode databases for important
47 groups such as Diptera.

48

49 Introduction

50 Recent studies have shown precipitous declines in insect populations, which can have far-reaching
51 consequences for ecosystem functioning and thus to human lives and livelihoods ([Basset and](#)
52 [Lamarre 2019](#); [Wagner 2020](#)). One of the striking features of this apparent decline is that it seems to
53 be affecting entire insect communities, rather than a few species of conservation concern or
54 particularly sensitive species groups ([Hallamann et al. 2017](#); [Bell et al. 2020](#); [Wagner 2020](#)). Because
55 of this, there is an urgent need to monitor whole insect communities and to understand the main
56 drivers of community change over a range of spatial and temporal scales ([Sánchez-Bayo and](#)
57 [Wyckhuys 2019](#)). This task is challenging due to taxonomic impediment (sensu, e.g., [Ebach et al.](#)
58 [2011](#)), which makes it hard to describe the huge diversity of insect communities with conventional
59 methods in a cost-effective way.

60 The advent of next-generation DNA sequencing coupled with metabarcoding approaches is
61 revolutionising the study of diverse insect communities by overcoming taxonomic impediment,
62 allowing the cost-effective processing of hundreds to thousands of complex mixed community
63 samples at high taxonomic resolution ([Douglas et al. 2012](#); [Barsoum et al. 2019](#); [Gueuning et al.](#)
64 [2019](#); [Piper et al. 2019](#)). Typically, metabarcoding studies of communities of insects and other
65 invertebrates involve the collection of field samples using a variety of methods, and then DNA from
66 multi-species samples is extracted, amplified using PCR and sequenced using a next-generation
67 sequencing platform (e.g. [Braukmann et al. 2019](#); [Marquina et al. 2019](#); [Zenker 2020](#)). Sequencing
68 data is used to produce a list of taxa recorded at each site, using bioinformatic pipelines and
69 reference libraries of DNA barcodes ([Marquina et al. 2019](#); [Zenker 2020](#)). Applications of this general
70 approach are increasing, particularly in the case of freshwater communities (e.g., [Elbrecht et al.](#)
71 [2017](#); [Bush et al. 2020](#)), where efforts are underway to develop standardised metabarcoding
72 approaches to be used in official monitoring programs such as the European Water Framework
73 Directive ([Hering et al. 2018](#)). The use of metabarcoding in studies of terrestrial insects has lagged
74 behind that of freshwater communities, but the technique has already been tested, for instance, in
75 the monitoring of wild bees ([Gueuning et al. 2019](#)), invasive species ([Piper et al. 2019](#)) and dung
76 insects for ecotoxicological assessments ([Blanckenhorn et al. 2016](#)), among many others. Despite
77 these advances, however, considerable efforts are still needed to develop, optimise and standardise
78 efficient methods to collect and process insect samples for DNA metabarcoding studies and
79 monitoring programs, as results are conditional on methodological alternatives adopted, including
80 DNA extraction, primer sets and bioinformatic pipelines ([Brandon-Mong et al. 2016](#); [Braukman et al.](#)
81 [2019](#); [Elbrecht et al. 2019](#)).

82 To the best of our knowledge, DNA metabarcoding has yet to be used for describing communities of
83 nocturnal insects, possibly due to the bias of ecologists towards studying daytime phenomena
84 ([Gaston 2019](#)). This is regrettable, because nocturnal insects encompass about half of all insect
85 species, and they can be negatively impacted by factors that do not operate during the day, such as
86 light pollution ([Owens et al. 2020](#)). Furthermore, they are key components of natural and
87 anthropogenic ecosystems, playing significant roles as, for instance, pollinators ([Macgregor et al.](#)
88 [2015](#)), crop pests ([Aizpurua et al. 2018](#)) and food resources for bats and other species ([Sierro et al.](#)
89 [2001](#); [Mata et al. 2016](#); [Aizpurua et al. 2018](#)). Although nocturnal insects are often captured in
90 passive traps aimed at sampling whole insect communities, these are often biased against some
91 taxonomic groups. For instance, Malaise traps in combination with DNA barcoding or metabarcoding
92 are increasingly used to survey insect communities worldwide ([de Waard et al. 2019](#)), but they are
93 mainly effective at collecting Diptera and Hymenoptera ([Matthews & Matthews 1971](#)), and thus can
94 underrepresent major nocturnal species groups such as moths (Lepidoptera). To overcome these
95 limitations, studying nocturnal insect communities requires targeted sampling devices, which in the
96 case of flying species normally involve light trapping combined with flight interception ([Young 2005](#);
97 [Häuser and Riede 2015](#)). The variety of light traps available is very large, ranging from commercial to
98 customised models, and from models that are operated manually to automatic models with triggers
99 that switch them on and off at specific times ([Young 2005](#); [Häuser and Riede 2015](#)). Typically, a light
100 trap can collect hundreds to thousands of individuals in a single night, and so DNA metabarcoding
101 could help speed up and increase the taxonomic resolution of sample processing ([Zenker et al. 2020](#)).
102 However, efforts are still needed to develop and optimise traps that can be efficiently combined with
103 metabarcoding in large scale field surveys. Methods that can avoid the need of hand-picking
104 individual specimens, thus reducing effort and contamination risks, and the use of chemical
105 compounds to kill or otherwise retain insects within traps, which would make the subsequent steps
106 of DNA extraction and amplification more difficult ([Dillon et al. 1996](#); [Ballare 2019](#)), would be
107 particularly useful.

108 In this study, we describe a methodological pipeline to study nocturnal flying insects, which combines
109 an automatic light trap device and DNA metabarcoding. Specifically, the study aims to: (i) describe
110 the light trap and its operation; (ii) determine its capacity in sampling a high diversity of insects in
111 short periods of time; and (iii) test whether the molecular procedures yield estimates of species
112 richness and composition comparable to those obtained using conventional morphological
113 identification. Overall, the study shows the value of our new approach to facilitate the sampling of
114 highly diverse communities of nocturnal flying insects in a short time.

115

116 **Materials and Methods**

117 **Study design**

118 We conducted field testing of the customised light trap in July 2017, within a protected area in north-
119 eastern Portugal (Parque Natural Regional do Vale do Tua; 41.33 N, 7.35 W). We collected a total of
120 12 arthropod bulk samples, by setting 6 light traps in each of two nights in two areas of cork oak
121 woodlands, which were expected to yield high insect diversity. The light traps were spread out so
122 that they were not visible from one trap to the other. Evaluation of metabarcoding results used the
123 12 field samples, involving comparisons of species richness and composition estimated through
124 molecular procedures *versus* conventional morphotaxonomy. We focused on species of moths
125 (Lepidoptera) because this is a taxonomically and functionally highly diverse and relatively well-
126 known group in the country (Corley 2015), there was a highly experienced taxonomist (MFVC)
127 available to undertake the field identifications, and a comprehensive library of DNA barcodes was
128 already available for a large proportion of moth species occurring in the region. Comparisons
129 between morphological and molecular results involved three different approaches to produce the
130 bulk samples, each representing a particular study design and objectives: (i) ‘individuals’ – bulk
131 sample for each site produced using one individual per species present in the field sample, which can
132 be used for studies targeting a single taxonomic group, and thus where metabarcoding of the entire
133 bulk sample is unnecessary and may eventually introduce biases; (ii) ‘legs’ – bulk sample similar to (i),
134 but including only one leg from each individual instead of the entire specimen, which may be used
135 when the individuals need to be preserved for other analysis or PCR inhibitors are likely to be present
136 in digestive tract or other tissues; and (iii) ‘mixture’ - bulk sample retaining all specimens collected,
137 without any sorting and irrespective of taxa. In our case, the approach (iii) excluded the individuals
138 retained for (i) and (ii), and thus did not consider the rarest species (i.e., represented by a single
139 individual in the field sample).

140 **Light trap design and operation**

141 We adapted a light trap device to allow daily deployment and automatic operation of many traps by
142 a small field team ([Figure 1](#)). Each light trap is equipped with one-meter long IP65 3528 UV LED light
143 strip of 395-405 nm, containing 60 LEDs of 0.08 W each, folded in three sections within a 35 cm long
144 transparent plastic tube with 3 cm diameter, and powered by a 12 Ah 12 V lead battery. UV light was
145 used because it is more efficient than other light sources at attracting Lepidoptera ([Young 2005](#)),
146 which was the main focus of our study. The strip is connected to a solar light sensor that
147 automatically activates the circuit at sunset and shuts it down at sunrise, enabling the placement of
148 several traps throughout daytime while ensuring an equal functioning time for each of them

149 throughout the night, avoiding bias regarding flight time activity and unnecessary draining of the
150 battery during the day. The plastic tube is installed in the centre of 3-4 acrylic plates (50 cm x 16.6 cm
151 x 2.5 mm), to intercept flying insects, and on top of a transparent funnel made of rigid 0.75 mm PVC
152 film with a 4 cm diameter opening that leads into a 30 L bucket. Inside the bucket there is a
153 breathable fabric bag containing cardboard egg boxes for the insects to rest and hide. Flying insects
154 attracted to the light collide with the acrylic plates and eventually fall through the tunnel and get
155 trapped inside the bucket bag. Each trap is visited in early morning by the field team, usually within
156 one hour after dawn.

157 **Sample processing and DNA extraction**

158 We designed the sample processing and DNA extraction approaches to speed up processing time,
159 reduce contamination risks and maximise DNA recovery from bulk samples. During the early-morning
160 visit to each trap, the bag was removed from the bucket, sealed with a rubber band and frozen for at
161 least three hours at -20 °C to immobilize the collected specimens. Each frozen sample was then
162 thawed at room temperature. All specimens were inspected and morphological identification was
163 attempted by a specialist (MFVC). No specimen was dissected to fully validate species identification,
164 as the objective was to compare regular ecological studies based on simple visual identification of
165 live moths with metabarcoding approaches. One specimen of each species identified per sample was
166 transferred into a 50 mL falcon tube to constitute the “individual” bulk sample. From these selected
167 specimens, a leg was removed from each and transferred into a second falcon to make up the “leg”
168 bulk sample. Finally, all the remaining specimens (both identified and unidentified) were transferred
169 to a third falcon to constitute the ‘mixture’ bulk sample. When very large insects (>5 cm body length)
170 were collected, only legs were retained in the bulks to avoid biases in DNA amplification (i.e.,
171 overrepresentation of species with high biomass, and masking of rare and low biomass species). The
172 36 falcon tubes (three per sample) were filled with 96% ethanol and stored at room temperature
173 until further processing. Maximum care was taken when handling specimens to avoid cross-
174 contamination among samples, namely by thoroughly cleaning all materials used (tweezers and
175 spatulas). Prior to DNA extraction, the ethanol was filtered out and the bulks were dried to constant
176 weight in an incubator at 56 °C for about 2 days. Afterwards, each ‘individual’ and ‘mixture’ bulk
177 sample was homogenized into a fine powder using the Bullet Blender 50-DX homogenizer (Next
178 Advance, USA), with 4 glass beads of 8 mm diameter during 15 min. DNA from ‘leg’ bulk samples was
179 extracted without further processing. DNA extraction was done using the E.Z.N.A.® Tissue DNA Kit,
180 following an adapted protocol (Supplementary Methods). We performed up to 3 DNA extractions per
181 sample (replicates), each one using 80 to 100 mg of the homogenized insect powder to increase

182 species detection. In one sample (SL6) only one 'individual' and two 'mixture' replicates were
183 possible due to low biomass.

184 **Metabarcoding library prep**

185 DNA extracts were diluted 1:100 (after a small test comparing PCR amplification success at different
186 dilutions) and amplified using the BF2-BR2 primer pair (Elbrecht and Leese 2017) in three
187 independent reactions. PCR reactions comprised 5 µl of Qiagen Multiplex Master Mix, 0.3 µl of each
188 10 nM primer, 3.4 µl of H₂O and 1 µl of diluted DNA. Cycling conditions consisted of initial denaturing
189 at 95 °C for 15 min, followed by 35 cycles of denaturing at 95 °C for 30 s, annealing at 45 °C for 30 s
190 and extension at 72 °C for 30 s, with final elongation at 60 °C for 10 min. The PCR products were
191 tested in 2% agarose gel to check for the amplification success. All PCR products were diluted 1:4
192 with water and further subjected to a second PCR reaction in order to incorporate 7 bp long
193 identification tags and Illumina P5 and P7 adaptors. PCR reactions were similar to that of first PCR,
194 except that 5 µl of Phusion Hot Start Flex 2X Master Mix (NEB) was used, as well as 0.5 µl of each 10
195 nM indexing primer. Cycling conditions consisted of initial denaturing at 98 °C for 2 min, followed by
196 8 cycles of denaturing at 98 °C for 5 s, annealing at 55 °C for 20 s and extension at 72 °C for 20 s, with
197 a final elongation at 72 °C for 1 min. PCR products were purified using Agencourt AMPure XP beads
198 (Beckman Coulter) in a 1:0.8 ratio, quantified using Nanodrop and diluted to 15 nM. Purified and
199 normalized PCR products were further pooled into a single library and quantified using qPCR (KAPA
200 Library Quant Kit qPCR Mix, Bio-Rad iCycler). The final library was diluted to 4 nM and sequenced in
201 an Illumina HiSeq 2500 Platform using a 2x250bp RapidRun kit for an average coverage of 160,000
202 paired reads per PCR product.

203 **Bioinformatic pipeline**

204 General sequence processing was carried out using OBITools (Boyer et al. 2016), along with VSEARCH
205 (Rognes et al. 2016) and LULU (Frøslev et al. 2017) for denoising. First, paired-end reads were aligned
206 using the command 'illumina-paired-end' and discarded if overlapping quality was less than 40.
207 Second, reads were assigned to samples and primer sequences were removed using 'ngsfilter',
208 allowing a total of 4 mismatches to the expected primer sequence. Finally, reads were collapsed into
209 haplotypes using the 'obiuniq' command and singletons (haplotypes with only one read per sample)
210 were removed. The remaining haplotypes left per sample were all joined in a single file and again
211 dereplicated. The '--cluster_unoise' VSEARCH command was then used to denoise the dataset by
212 removing spurious sequences resultant from PCR and sequencing errors, followed by the command '-
213 -uchime3_denovo' to remove potential chimeric sequences. Afterwards, the remaining sequences
214 were clustered at a 99% similarity threshold and the original reads were mapped back to the

215 remaining haplotypes. Finally, we used LULU to remove genetically similar co-occurring haplotypes,
216 this way highly reducing the number of mitochondrial nuclear copies present in the final dataset that
217 tend to artificially increase the number of molecular units and taxa.

218 All haplotypes retained after the bioinformatic processing, were identified to the lowest possible
219 taxonomic level, considering both moths (Lepidoptera) and other arthropod groups. The taxonomic
220 assignment of each haplotype to a taxon was done with the support of a neighbour-joining
221 phylogenetic tree based on an alignment of the haplotypes sorted by their read count. This allowed
222 to visually define clusters of haplotypes that corresponded to the same taxon, as well as to identify
223 chimeric sequences and PCR errors that remained in the dataset. Taxa were identified by comparing
224 the representative haplotypes of each cluster against online databases (BOLD and NCBI), as well as
225 unpublished sequences of arthropods collected in northern Portugal (InBIO Barcoding Initiative; e.g.,
226 [Ferreira et al. 2020](#)). Species level identifications were usually made for similarity values above 98.5%
227 ([da Silva et al. 2019](#)), except in rare cases where no other species of the genus are known to exist,
228 and thus genetic divergence reflects local haplotype diversity. Whenever a haplotype matched
229 several species, genus, or families at similar identity levels, we selected the most inclusive taxonomic
230 rank. For example, if a haplotype matched with 95% similarity two species of different genus
231 belonging to the same family, we identified it only to family level. Those that best matched the same
232 taxa were collapsed into a single taxon, as we assumed that they belonged to the same OTU.
233 Haplotypes whose identification was only possible up to family, order or class level were clustered
234 according to their similarity into distinct taxa (e.g., Noctuidae 1, Noctuidae 2, and so on). All
235 identifications were checked for plausibility, considering the species geographical ranges and
236 seasonal flight periods. Implausible identifications (e.g., species from other biogeographic regions not
237 known to occur in the Iberian Peninsula), were reviewed and moved if needed to a higher taxonomic
238 rank (e.g., from species to genus level).

239 **Statistical analysis**

240 We compared both Lepidoptera richness and composition between morphological identification and
241 metabarcoding approaches for each type of bulk sample. For Lepidoptera richness we applied a
242 generalized linear mixed model (GLMM) with a gaussian distribution using the function 'lmer', and
243 with light trap as random variable. Statistical significance ($p < 0.05$) of the model was tested with a
244 likelihood ratio test using the function 'anova'. To compare the species composition between the
245 different treatments we first calculated a Jaccard distance matrix based on presence/absence
246 records of Lepidoptera taxa in each sample, and then performed a permutational multivariate
247 analysis of variance (PerMANOVA) using the function 'adonis'. All statistical analyses were done in R

248 version 3.5.2 (R Core Team 2018) using packages lme4 (Bates et al. 2015) and vegan (Oksanen et al.
249 2018).

250 **Results**

251 **Trap operation and morphological identification**

252 All traps operated as planned, showing their effectiveness at collecting a large number of nocturnal
253 flying insects. Sorting of the bulk samples to extract Lepidoptera for subsequent comparisons with
254 metabarcoding yielded a total of 871 identifiable individuals (average \pm SD of 72.6 ± 23.0 individuals
255 per sample), which were assigned to a minimum of 102 species (26.8 ± 6.7 species per sample)
256 (Supplementary Table S1). Some specimens could not be identified visually as wing scales were
257 largely absent and coloration patterns were no longer observable. A total of seven species accounted
258 for 52.4% of the individuals identified, while 41 species were represented by a single individual. The
259 individuals identified were then used to produce the bulk samples for comparison with
260 metabarcoding. All 102 species were considered in the 'individuals' and 'legs' bulk samples, while the
261 'mixture' bulk samples included only 40 recognizable species (11.9 ± 3.6 species per sample) after
262 removing the individuals to produce the former two bulks. However, in the 'mixture' bulk there were
263 also the unidentifiable individuals, which were too damaged or otherwise lacked diagnostic features
264 required for species level identification.

265 **Metabarcoding results**

266 Considering the overall results for the three bulk types ('individuals', 'legs' and 'mixture'), sequencing
267 of libraries generated a total of 47,764,194 paired reads, with an average (\pm SD) of $151,632 \pm 81,181$
268 per PCR product. After bioinformatic filtering, we retained a total of 14,484,254 paired reads, with an
269 average of $46,573 \pm 30,371$ per PCR product.

270 In the mixture bulk sample, we detected a total of 528 arthropod taxa (124.5 ± 33.3 taxa per sample),
271 of which 61.2% were identified to species, 10.6% to genus, and 28.2% to family or higher taxonomic
272 ranks. Most taxa detected belonged to Lepidoptera (31.1%), Diptera (26.1%) and 42.8% to 14 other
273 orders (Figure 2). In the case of Lepidoptera, which were the main focus of this study, we detected a
274 total of 189 taxa (55.2 ± 13.7 taxa per sample), of which 111 taxa (26.8 ± 8.1 taxa per sample) were
275 represented in the 'individuals' bulk, 106 taxa (26.3 ± 6.7 taxa per sample) in the 'legs' bulk, and 164
276 taxa (45.8 ± 12.7 taxa per sample) in the 'mixture' bulk sample (Supplementary Table S1).

277 **Comparisons between morphological identification and metabarcoding**

278 Considering the Lepidoptera, comparisons between morphological and metabarcoding results were
279 largely similar for the ‘individuals’ and ‘legs’ bulks, both in terms of species richness per sample ($\chi^2 =$
280 1.3838, $df = 2$, $p = 0.5006$) and species composition (pseudo-F = 0.8399, $df = 2$, $R^2 = 0.0484$, $p =$
281 0.7373). The overall number of species detected was slightly higher for metabarcoding than for
282 morphology, both for ‘individuals’ (111 vs. 102) and ‘legs’ (106 vs. 102) bulks. The mean percentage
283 of species detected by both methods per sample was similar for the ‘individuals’ (64.6%±6.2%, 54.8-
284 75.0%) and ‘legs’ (67.4%±6.2%, 59.4-77.4%) bulks, with similar values also for the mean percentage
285 of species detected by morphology but not by metabarcoding (‘individuals’: 18.3%±5.0%, 11.4-29.0%;
286 ‘legs’: 17.3%±3.6%, 11.8-21.9%), and vice versa (‘individuals’: 17.1%±5.0%, 11.1-28.1%; ‘legs’:
287 15.3%±3.2%, 9.7-20.0%). When considering only families normally assigned to macrolepidoptera
288 (e.g., Erebidae, Geometridae, Noctuidae), the percentage of species shared between methods
289 increased for both the ‘individuals’ (72.3%±10.5%, 54.5-86.4%) and ‘legs’ (74.9%±10.4%, 60.0-90.5%)
290 bulks, while in microlepidoptera it reduced in both cases (‘individuals’: 55.4%±14.9%, 31.3-85.7%;
291 ‘legs’: 58.7%±16.0%, 38.9-100.0%). Many of the mismatches observed were thus caused by
292 microlepidoptera species, mainly due to species of the same genus identified differently by
293 morphological and molecular methods, to taxa that could be identified unambiguously to species
294 level by one method but not the other, and to more species of the same genus being detected by
295 one of the methods. For instance, while morphology detected *Apatema mediopallidum*,
296 metabarcoding detected only two unidentified *Apatema* species that did not match the DNA barcode
297 of *A. mediopallidum* currently available in the databases. Likewise, morphological examination
298 detected *Scopula submutata* and *Scythris parafuscoaenea*, while metabarcoding detected *Scopula*
299 *marginepunctata* and *Scythris dissimilella*, respectively. Examples of differences in identification
300 resolution included *Eurodachtha canigella* detected by morphology and *Eurodachtha*
301 *siculella/canigella* by metabarcoding, while morphology detected an unidentified *Depressaria* while
302 metabarcoding detected *Depressaria adustatella*. Finally, common mismatches occurred with species
303 belonging to the genus *Idaea* and the family Brachodidae, with morphology recording *Idaea*
304 *belemiata*, *Brachodes gaditana* and *Agonopterix scopariella*, and metabarcoding detecting *I.*
305 *obsoletaria* instead of *belemiata*, *Brachodes gaditana* plus *B. funebris*, and *A. atomella* instead of *A.*
306 *scopariella*.

307 In comparisons involving the ‘mixture’ bulk sample, morphology and metabarcoding recovered a
308 significantly different community of moths. Not only the average species richness identified per
309 sample was different ($\chi^2 = 111.46$, $df = 1$, $p < 0.0001$), but also the species composition (pseudo-F =
310 6.0464, $df = 1$, $R^2 = 0.2156$, $p = 0.001$). The percentage of species detected by both methods was only
311 20.9%±5.5% (11.3-28.1%), with 74.6%±6.7% (64.3-83.0%) of species detected through metabarcoding

312 but not morphology, while only $4.6\pm 2.1\%$ (1.9-9.5%) of species were detected by morphology but
313 not by metabarcoding. As for the other two bulks, the percentage of species detected by both
314 methods was higher for macrolepidoptera ($34.6\pm 14.6\%$, 10.0-58.3%) vs. microlepidoptera
315 ($12.8\pm 7.5\%$, 5.0-31.6%).

316 Discussion

317 Our study provides an effective pipeline for large scale sampling of nocturnal flying insects, from field
318 sampling using a customised trap design, through lab processing of samples, to bioinformatic analysis
319 of sequencing data. The trap we customized proved to be successful at collecting a large number of
320 nocturnal insects, from which bulk samples for subsequent metabarcoding processing can be easily
321 obtained with minimal risks of contamination. We found that metabarcoding and morphological
322 identification provide similar results when comparing bulk samples with relatively few individuals of
323 known species, but that metabarcoding detects far more species when dealing with complex
324 mixtures (real samples) that include many individuals that cannot be easily identified through
325 morphological examination (e.g., due to specimen's age, small size and scale damage, this last one
326 probably accentuated by the transport to a freezer in a bag). Overall, we suggest that our
327 methodological pipeline can be widely applied in ecological studies, contributing to improve our
328 understanding of the trends and drivers of nocturnal insect communities and complement studies
329 based on Malaise traps that are not so efficient in capturing Lepidoptera and other insects like
330 Coleoptera, Mantodea, Neuroptera, Orthoptera and Hemiptera ([Matthews & Matthews 1971](#)).

331 The trap customized in our study shares many similarities to others used elsewhere ([Zenke et al.](#)
332 [2020](#)), including traps that are available commercially. However, it has the advantage of being
333 relatively cheap and easy to produce, which makes it suitable for large scale field studies where
334 resources are limited, and a large number of sites need to be sampled. Furthermore, the trap was
335 adapted to retain insects without the need to use any chemical product to kill the individuals, which
336 likely facilitates the subsequent steps of DNA extraction and amplification ([Dillon et al. 1996](#); [Ballare](#)
337 [2019](#)). Finally, the use of a breathable fabric bag makes it easier to extract insects from the trap and
338 to undertake the initial processing steps in the field with minimal handling of samples, thereby
339 reducing the risks of contamination across samples. Despite these advantages, however, it is
340 necessary to bear in mind some limitations and potential shortcomings, which are similar to those
341 already described for light traps in general. For instance, light traps only sample part of the nocturnal
342 flying insect community, as many species are not attracted to light and/or have no nocturnal activity
343 and thus cannot be represented in the samples ([Young 2005](#)). Also, the area effectively sampled by a
344 light trap (i.e., trapping radius) may be conditional on vegetation density affecting penetration of the

345 light source (Bowden 1982), with traps set in areas with higher visibility (e.g., grasslands) possibly
346 attracting individuals from farther away than those set in more cluttered habitats (e.g., forests and
347 shrublands). Therefore, when designing a study based on light traps such as ours, researchers need
348 to be aware of these and other potential constraints, using best practices developed from previous
349 studies to control or correct eventual sampling biases (Bowden 1982, Young 2005).

350 The comparisons of species composition between morphological identification and metabarcoding
351 revealed a reasonable matching when using the ‘individuals’ and ‘legs’ bulk samples. Nevertheless,
352 about 35% of the species occurrences were non-congruent between methods, likely due to
353 limitations of species identification using morphology, metabarcoding, or both. A significant part of
354 the mismatches was probably due to the difficulties of morphological identification of small
355 microlepidoptera species, as species occurrences detected with both methods raised markedly from
356 micro- to macrolepidoptera. Because of these difficulties, morphological examination sometimes
357 assigned an individual to a species while metabarcoding recorded another similar species from the
358 same genus. In a few cases, mismatches involved morphology assigning several similar individuals to
359 the same species, while metabarcoding revealed that a few of these belonged to a second or even a
360 third species. These results point out the limitations of using morphological examination as the
361 benchmark for metabarcoding validation, even in cases such as ours where the fauna studied was
362 reasonably well known (Corley 2015), and a very experienced specialist was involved in the study (M.
363 F. V. Corley). This is in line with the results of recent efforts to DNA barcode the Portuguese moth
364 fauna, which has revealed several new species, some of which had been previously misidentified
365 (e.g., Corley & Ferreira 2019, Corley et al. 2019). In a few cases, mismatches were associated with
366 limitations of metabarcoding, with the markers used being unable to discriminate between closely
367 related species, while morphology readily provided species-level identifications. Metabarcoding also
368 failed to identify species for which there were no DNA barcodes available at the time of the study,
369 which is a general problem affecting metabarcoding studies. Finally, metabarcoding possibly
370 produced a few false positives, such as *Agrotis bigramma*, *Leucochlaena oditis* and *Luperina*
371 *Testacea*, as these species are known to fly only in late summer and early autumn while our samples
372 were collected in July. All these species were represented by just a few reads, and possibly resulted
373 from the assignment of reads to incorrect samples (cross-talk) (e.g., Edgar 2018), as our samples
374 were run together with light trap samples collected in September. Overall, therefore, these
375 comparisons suggest that metabarcoding provided an accurate description of the communities
376 represented in the ‘individuals’ and ‘legs’ bulk samples, with most errors resulting from problems of
377 unresolved taxonomy or incomplete databases, though there might have been errors associated with
378 metabarcoding itself.

379 Comparisons between morphology and metabarcoding involving the ‘mixture’ bulk sample provided
380 the lowest congruence levels in species occurrences. Errors were mainly due to metabarcoding
381 detecting a large number of species not recorded through morphology, while only a very few species
382 were detected through morphology but not metabarcoding. These results are likely a consequence of
383 the ‘mixture’ bulks retaining many small individuals from unidentified species, particularly
384 microlepidoptera, which contributed to increase taxonomic diversity. Furthermore, there were
385 probably body parts retained in the mixture that could not be detected, let alone identified, and that
386 further contributed to increase diversity. Finally, some species could have been detected through the
387 stomach contents of carnivorous arthropods (Sheppard et al. 2005; da Silva et al. 2019), and not
388 directly through individuals collected in the trap. Additionally, although eventual problems of lab and
389 field contamination inflating numbers of taxa could not be totally discarded, we believe that these
390 should have had little influence in the results, as this problem was not detected for the ‘individuals’
391 and ‘legs’ bulks. Therefore, it is unlikely that the higher number of taxa recorded through
392 metabarcoding in ‘mixture’ bulks were false positives, except in the few cases involving cross talk
393 errors. Instead, the higher number of taxa likely reflected the much-increased sensitivity of
394 metabarcoding to estimate species diversity in relation to the conventional morphological approach.
395 This result also suggests that metabarcoding validation studies using only artificial mock communities
396 may be underestimating the true power of the technique to reveal the diversity of real communities,
397 and so the use in validation of actual field samples is highly recommended.

398 **Conclusions**

399 The customised light trap described in this study in combination with DNA metabarcoding offers a
400 relatively simple and cost-effective approach to describe communities of nocturnal flying insects in
401 large scale studies. Although like other approaches based on metabarcoding it cannot provide
402 information on species abundances (Elbrecht & Leese 2015; Piñol et al. 2015), it offers the ability to
403 process hundreds to thousands of samples at high taxonomic resolution in a relatively short time
404 frame, which can hardly be achieved through conventional morphological approaches (Ji et al. 2013).
405 A key advantage of our approach is that a large number of insect specimens can be collected at a
406 number of sites in a single night by a small field team (Zenke et al. 2020), which can be particularly
407 advantageous if the study is carried out in remote areas, while other sampling devices such as
408 Malaise traps are usually more labour intensive and require deployment in the field for much longer
409 periods (e.g., Matthews & Matthews 1971; Häuser & Riede 2015). Like any sampling device,
410 however, our method is biased towards some species groups such as flying Lepidoptera, Diptera and
411 Coleoptera that are attracted to light, and thus a combination of sampling methods should be used in
412 studies requiring a comprehensive account of entire insect communities (e.g., Yang et al. 2014,

413 [Marquina et al. 2019](#)). To further enhance the value of our approach, it would be important to
414 increase the DNA barcode reference databases for hyper-diverse insect groups such as Diptera (e.g.,
415 [Ferreira et al 2020](#)), to apply bioinformatic procedures correcting for cross talk problems causing
416 false positives in metabarcoding (e.g., [Edgar 2018](#)), to standardise procedures that may affect
417 catchability of different insect groups such as for instance the light source and intensity, and the
418 weather and moonlight conditions ([Young 2005](#)), and to further assess potential errors and
419 limitations such as variations in effective catching distance across habitats with different vegetation
420 cluttering (e.g., forests with or without undergrowth; [Young 2005](#)). Overall, we suggest that the
421 methodological pipeline proposed in this study provides a convenient approach for the standardised
422 monitoring of spatio-temporal variations in the diversity and composition of complex nocturnal
423 insect communities, with the potential to help addressing pressing societal challenges such as global
424 insect declines.

425

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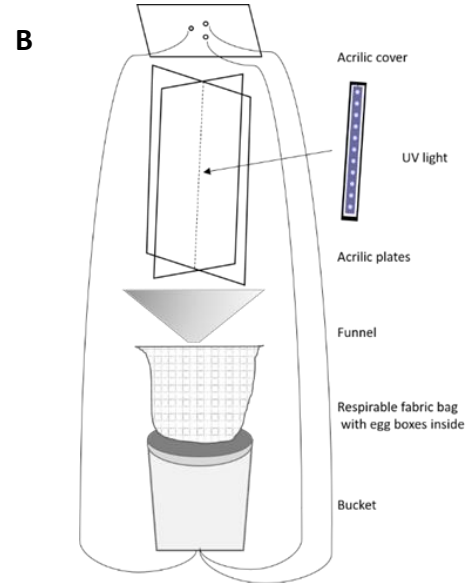
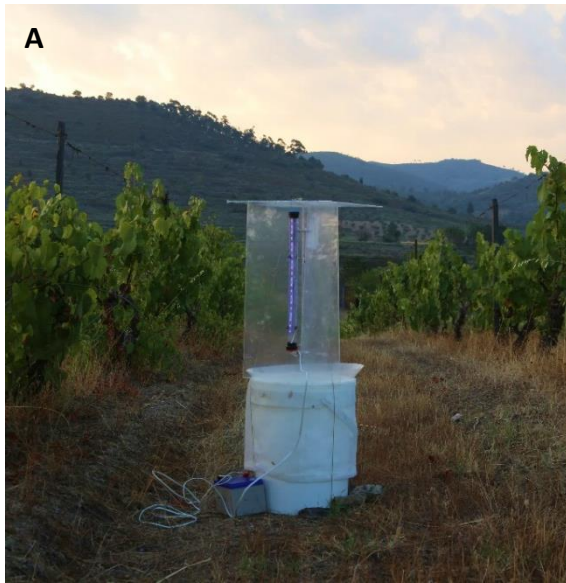
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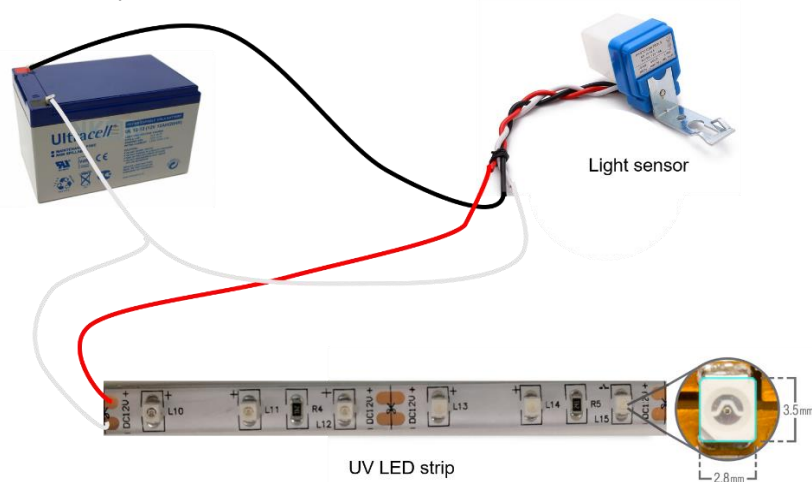
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569 **FIGURES**

570



572 **C** 12V Battery

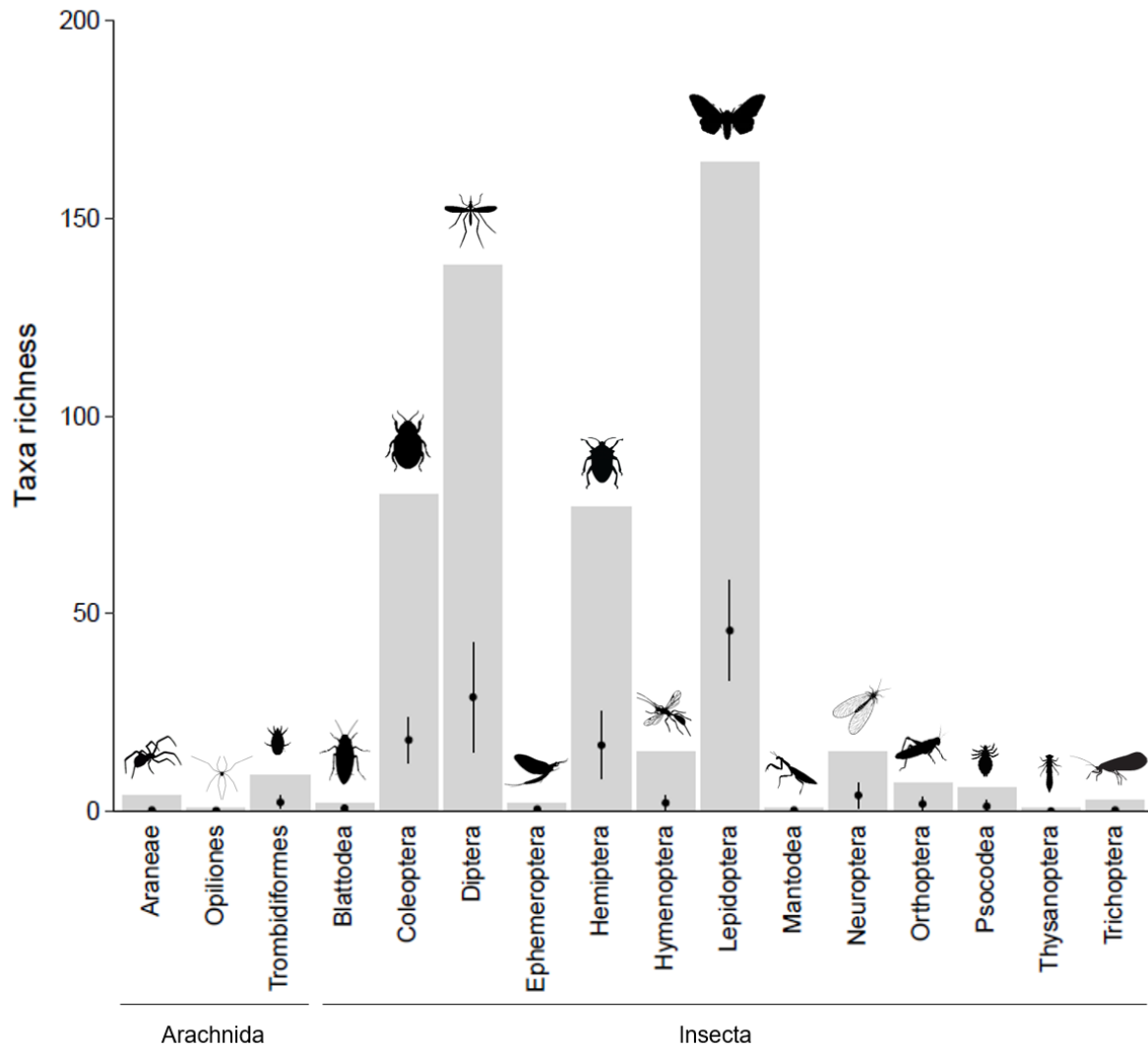


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574

575 **Figure 1.** Customised UV light traps designed to collect night flying insects, showing a trap ready to
576 operate in the field (A), a schematic representation of the assembly of all the pieces making up the
577 complete trapping system (B), and the electric components of the trap and how to connect them (C).

578



578

579 **Figure 2.** Taxa richness detected through metabarcoding in the 'mixture' bulk samples. Grey bars
580 represent the total number of taxa detected per taxonomic order in the sum of all 12 samples.
581 Whiskers represent the average \pm sd number of taxa detected per sample.