

Delivering on a promise: Futureproofing automated insect monitoring methods

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Abstract

Due to rapid technological innovations, the automated monitoring of insect assemblages comes within reach. However, this continuous innovation endangers the methodological continuity needed for calculating reliable biodiversity trends in the future.

Maintaining methodological continuity over prolonged periods of time is not trivial, since technology improves, reference libraries grow, and both the hard- and software used now may no longer be available in the future. Moreover, because data on many species are collected at the same time, there will be no simple way of calibrating the outputs of old and new devices.

To ensure that reliable long-term biodiversity trends can be calculated using the collected data, I make four recommendations: (1) Construct devices to last decades, and have a five-year overlap period when devices are replaced. (2) Construct new devices to resemble the old ones, especially when some kind of attractant (e.g. light) is used. Keep extremely detailed metadata on collection, detection and identification methods, including attractants, to enable this. (3) Store the raw data (sounds, images, DNA extracts, radar/lidar detections) for future reprocessing with updated classification systems. (4) Enable forward and backward compatibility of the processed data, for example by in-silico data 'degradation' to match the older data quality.

Key words:

DNA barcoding, bioacoustics, computer vision, radar, lidar, monitoring, insects, arthropods, LTER

Main Text

The development of technological approaches for insect monitoring can allow unprecedented improvements in the spatial, temporal and taxonomic coverage of insect biodiversity assessments [1–4]. To meet the political, societal and industry needs for large-scale biomonitoring [5–7], these technologies can help close an important knowledge gap, since insects and other arthropods are the

37 most species rich group of animals on earth, and perform important ecosystem services (e.g. crop
38 pollination or decomposition) and disservices (e.g. disease transmission or crop damage). Insects are
39 notoriously underrepresented in biodiversity monitoring schemes, since monitoring their diversity
40 by traditional means with morphological identification is extremely time consuming and knowledge
41 intensive. Moreover, some of the largest insect groups, such as flies and parasitoid wasps, are even
42 within insect monitoring programs and ecological assessments rarely assessed. Automated
43 monitoring could thus make large-scale insect biodiversity monitoring possible for a fraction of the
44 effort and costs of traditional monitoring methods, and contribute to solving a number of identified
45 challenges to large scale biomonitoring [6].

46 However, in order to reliably document changes in species occurrences, population sizes and
47 biodiversity metrics over time, it is important to use the exact same method of monitoring over the
48 whole sampling period. This applies to the collection, detection and identification methods,
49 including any attractants used, as well as the taxonomic precision of the end product provided. This
50 sounds logical, and even trivial, but anyone who has tried to do a sustained monitoring of
51 biodiversity has learned that maintaining methodological continuity is not as easy as it sounds. Even
52 when funding for continuous monitoring is secured (which is challenging even in the richest of
53 countries), traps need to be replaced due to wear, loss or breakdown, workers learn to identify new
54 species, fall ill or make mistakes, and taxonomy changes over time. In addition, there is a constant
55 need for specialists with the right expertise, which is unfeasible in most parts of the world and for
56 most taxa. For this reason, consideration of the methodology and data quality needed, is best done
57 before monitoring commences.

58 Particularly when using high-tech devices and computer algorithms, the challenges to ensuring
59 methodological continuity compound:

- 60 i. The hardware and software used in these devices are rapidly evolving and improving:
61 camera sensitivity improves, barcoding pipelines change (Iwaszkiewicz-Eggebrecht this
62 issue [8]), energy use becomes more efficient, etc. Although it is almost a moral
63 imperative to use these developments to our advantage, and monitor as many species
64 as possible for the lowest costs, we must also recognize the consequences of these
65 developments for the long-term trends we're trying to calculate.
- 66 ii. Since the devices, which are often custom made for the purpose of insect monitoring,
67 depend on hard- and software produced by third parties, there is no guarantee that
68 these exact components will be available in the future. In fact, it is likely that they will
69 not, because, industrial suppliers have no incentive to produce obsolete products,
70 supply chains change, or new legislation may prevent the continued production or
71 import of specific components.
- 72 iii. Weathering and wear of (parts of) the devices and traps in the field may make repeated
73 use challenging, and parts may need to be exchanged regularly [see for example 9].
- 74 iv. The reference libraries of DNA barcodes, images and sounds used for classification are
75 constantly growing, and will contain more and more species, allowing more accurate
76 classification.
- 77 v. These devices are designed to collect multivariate data (dozens to thousands of species
78 at the same time), and therefore, there will be no simple calibration possible of
79 measured variables when monitoring devices are replaced with newer versions,
80 especially given the volatility of insect population dynamics and the prevalence of rare
81 species [10].

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83 In most cases, technological improvements will increase detection and/or identification rates, which,
84 when left unaccounted for, will lead to detecting a false increase in diversity over time. But any
85 change in detection rates of any species will affect the inferences one can draw from the monitoring
86 program in the future. The technologies covered in this Theme Issue (computer vision, DNA
87 (meta)barcoding, radar and acoustics) are still in development, and are thus particularly vulnerable
88 to the challenges outlined above. Although statistical methods may be able to account for some
89 aspects of methodological variability, the reliability of the calculated temporal trends will suffer
90 significantly from rapid methodological changes, in comparison to a continuous methodology..

91 I will illustrate the difficulties of ensuring methodological continuity over prolonged periods of time
92 by two examples that are orders of magnitude less complex than any of the technologies discussed
93 in this Theme Issue: Pitfall trapping of ground beetles (Coleoptera: Carabidae) with morphological
94 species identification. In the north of the Netherlands, a program for monitoring ground beetle
95 populations by means of standardized, year-round pitfall trapping was started in 1959 by the
96 workers of the Willem Beijerink Biological Station, part of what is now Wageningen University. They
97 started trapping ground beetles in custom-made square metal cans with an exact perimeter of 1m,
98 [11,12]. These traps were replaced in the 1980's and possibly at an earlier time as well, but
99 unfortunately this was not well documented. After the biological station was formally dissolved in
100 1998, the trapping program was continued by the volunteers of the WBBS foundation using the cans
101 constructed in the 1980's. By 2020, the traps were in need of replacement, and we acquired funding
102 for the construction of new traps.

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105 **Fig. 1.** The edges of the old (a) and the new (b) ground beetle traps. Due to technological changes,
106 the old, rounded, edge would be excessively hard to reproduce. We have aimed to make the edge as
107 similar as possible under field conditions (c). Photo's: Henk de Vries (a), Alje Woldering (b & c).

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109 Although we were unable to find back the company that constructed the original traps, this looked
110 like a straightforward construction job to us, which any metalworking company could do. However,
111 after numerous emails, phone calls and visits to various companies, we found that the technique for
112 constructing the rounded edge of the old cans (Fig. 1a), a process called 'edge beading', had fallen
113 out of use for this kind of sheet metal, and that a custom-made mold (a 'die') for a bead of exactly
114 this size would be excessively expensive (roughly half of our budget for replacing the traps). We
115 therefore had to settle for a different edge type for our new traps (Fig. 1b). We hope that, at least
116 from a beetle's perspective, there will be no difference between the trap types (Fig. 1c). We have
117 replaced the traps in two phases over 2022 and 2023 to test if and how the catch is affected by the
118 trap replacement.

119 A second example from the same monitoring program is the challenge we have faced regarding the
120 transition between data formats. All data collected on a weekly basis from 1959 to 1998 were once
121 digitized, and stored on computer tapes. Currently, reading such tapes is close to impossible,
122 especially since we don't know which computer brand was used for data entry, or the software
123 format the data were stored in. Fortunately, all data are still available on paper sheets, and we are
124 currently working on redigitising these, where we ensure compatibility with the upcoming Humboldt
125 Extension for ecological inventories to the GBIF Darwin Core. That this is necessary illustrates the
126 importance of a timely transition between data formats as hard- and software evolve. In 2009, Borer
127 et al. [13] published some excellent advice on data management, and wrote: 'As hard as it is to
128 believe today, we can foresee the day when CD-ROMs might be difficult to read.'. As per 2023, that
129 day has come and gone, and it would be well advised to rapidly move all data stored on CD-roms and
130 DVD's to the cloud (or better, to make them openly accessible on a FAIR biodiversity data portal like
131 GBIF). This trend of soft- and hardware replacement is likely to continue, and it will be important to
132 keep up with these developments.

133 Now imagine going through a similar process for replacing a modern camera trap, a radar, a
134 sequencer or a barcoding pipeline, or to try to read data 20 years from now. Ideally, we would want
135 every single hard- and software component used for detecting and identifying organisms, and for
136 data storage to remain constant for as long as the monitoring lasts: several decades. But this is
137 exceedingly unlikely, since all technological insect monitoring methods depend on a chain of
138 industrial suppliers for the hard- and software used in the devices, as well as for data storage. These
139 suppliers have no interest in continuing the production of obsolete products, just as we, as end users
140 should use the best products available to monitor as many species as possible. Hence, we will need
141 other solutions to ensure methodological continuity.

142 Below, I make four concrete recommendations, from the level of device construction to the
143 processed biodiversity data, to ensure the data produced now can be used to calculate reliable
144 biodiversity trends in the future. These recommendations are in most cases not only applicable to
145 new technologies, but are equally useful for traditional insect monitoring programs:

- 146 a) Build to last. Design devices with the aim of lasting decades, and don't wait for them to
147 break down before replacing them. Ideally, aim for an overlap period of 5 years when
148 replacing devices, but here it should be considered that two traps set up in close proximity
149 may influence each other, especially when an attractant is used. In such cases, a phased
150 transition across multiple locations may be a better option.
- 151 b) Keep extremely detailed metadata, so that future devices can collect data in the same way,
152 even when the sensors improve. This is especially important when an attractant, such as
153 light or a colored screen is used, because a change in attractant(s) will inevitably affect
154 insect behavior. But also extreme metadata detail is required regarding the sensitivity of the
155 sensor(s), as this information can be used to make collected data more comparable.
156 Metadata should thus include the exact light spectrum (including parts of the light spectrum
157 that are not visible for humans, and luminosity of a light trap, exact screen color and texture
158 [see 14 this issue], motion triggers (if used), camera resolution, microphone sensitivity,
159 frequency range, and recording bitrate, sequencing depth, biochemical and bioinformatics
160 pipelines for (meta)barcoding [see 8 this issue], etc. In addition, all data on the operational
161 status of the traps and/or sensors, as well as the exact locations, should be recorded and
162 stored. Although a lack of historic metadata may prevent us from precisely redoing historical
163 investigations, we can make future resampling campaigns a lot more accurate.

- 164 c) Store all raw data (photos, condensed audio recordings, radar/lidar detections, barcoding
165 libraries, etc.) in a non-proprietary format for future reprocessing using new algorithms,
166 computational facilities and reference libraries. For this, a data infrastructure is needed that
167 can handle and process the expected volume of raw data, and that can ensure data
168 accessibility in the future. In addition, the energy, and thus environmental, costs of data
169 storage and reprocessing should be considered.
- 170 d) Ensure forward and/or backward compatibility of the processed data (data with assigned
171 taxonomic names), so that the quality of the data collected in the future can be made
172 comparable to the data collected now, regarding, for example, the taxonomic depth and the
173 sensor sensitivity. This may be done by either bringing currently collected data up to
174 standards of the future (which will possibly need reprocessing, see previous point), or by in-
175 silico degradation of future data to match the current standards (assuming that future data
176 will be of higher quality than current data). To make this possible, there is a strong need for
177 the automated taxonomic harmonization of species identifications. The GBIF taxonomic
178 backbone, which is based the Catalogue of Life [15], the Barcode Index Numbers from the
179 Barcode of Life project [16], and 103 other taxonomic resources [17], seems the most
180 promising resource for automated harmonization with the most up-to-date taxonomic
181 classification for both traditional and genetic data.

182 These recommendations do not only apply to the monitoring of insects, but to any type of
183 automated biodiversity monitoring, for example camera trapping of mammals, acoustic monitoring
184 of birds, bats, whales or fish, eDNA, or bird radar.

185 **Conclusions**

186 If the difficulties of securing long-term funding for biodiversity monitoring and the continued
187 training of taxonomic specialists can be overcome, the technological developments of the past
188 decades bring large-scale insect monitoring is closer than ever. But before we start deploying
189 devices whenever an opportunity arises, it will pay off to first consider how we want to use these
190 data now and in the future. What we can learn and infer, and for whom and for what purpose the
191 data will be useful, will crucially depend on the choices we make today. For many purposes,
192 including conservation planning and pest monitoring, accurate species level identifications are of
193 crucial importance. Likewise, for calculating long-term trends, methodological continuity is crucial. If
194 the above recommendations are followed, I am confident that automated insect monitoring will
195 yield us many insights about the changes in insect biodiversity over the coming decades.

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