

# 1 Expanding the sentinel approach through 2 multimodal integration: resolving 3 underlying ecological processes with 4 eDNA and computer vision

5 Yuval Cohen\*<sup>1,2</sup>, Jordan P. Cuff\*<sup>3</sup>, Liora Shaltiel-Harpaz<sup>1,4</sup>

6 <sup>1</sup>Northern Agriculture R&D, MIGAL – Galilee Research Institute, Kiryat Shmona, Israel

7 <sup>2</sup>Department of Evolutionary and Environmental Biology, Faculty of Natural Science and Institute  
8 of Evolution, University of Haifa, Haifa, Israel

9 <sup>3</sup>School of Natural and Environmental Sciences, Newcastle University, Newcastle-upon-Tyne,  
10 NE1 7RU, United Kingdom

11 <sup>4</sup>Environmental Studies Department, Tel-Hai University of Kiryat Shmona in the Galilee, Kiryat  
12 Shmona, Israel

13 \*Equal contribution

14 Correspondence at: [jordancuff@gmail.com](mailto:jordancuff@gmail.com), [uvicohen@gmail.com](mailto:uvicohen@gmail.com), [liora@migal.org.il](mailto:liora@migal.org.il)

## 15 **Abstract**

16 Sentinel approaches provide a semi-controlled method for quantifying in-field ecological  
17 interactions and processes while reducing bias and labour. They are, however, limited by  
18 difficulties ascribing taxonomic identities, behavioural context and temporal resolution to  
19 interacting agents. The integration of additional sources of data, including the analysis of  
20 DNA left behind on sentinel objects and the use of cameras to observe interactions,

21 presents a valuable extension of sentinel approaches. Several considerations, limitations  
22 and obstacles may nevertheless hinder this multimodal integration.

23 Here, we describe the added value that multimodal integration presents for sentinel  
24 approaches, focusing on the application of eDNA analysis and camera deployment. The  
25 analysis of DNA left on sentinel objects, adjacent substrates or collected from interacting  
26 agents themselves presents an opportunity to enhance the taxonomic resolution of  
27 sentinel-agent interactions. Similarly, the deployment of cameras, especially integrated  
28 with advances in computer vision and deep learning, can enhance the temporal resolution  
29 and behavioural context derived from sentinel approaches.

30 Integrating these monitoring modalities into sentinel approaches will significantly advance  
31 the taxonomic, temporal and functional resolution of such studies, but we also  
32 acknowledge that this added value is dependent on the specific hypotheses and needs  
33 of each study. We discuss the contexts in which multimodal expansion of sentinel  
34 approaches should be considered and prioritised. Through the integration of eDNA,  
35 cameras, deep learning and broader emerging technologies, we posit that sentinel  
36 approaches can transcend a simplistic method for quantifying processes and become a  
37 data-rich approach for mechanistic insight into a range of ecological interactions.

38

39 *Keywords: biomonitoring, camera trap, deep learning, environmental DNA, merged*  
40 *methods, network ecology, predator-prey, trophic interactions*

41

## 42 **Introduction: from the outcomes of ecological processes to** 43 **agents and their behaviour**

44 Ecological interactions underpin a vast array of functions and processes, ultimately  
45 determining the stability and resilience of ecosystems (Thébault & Loreau, 2005). In a  
46 rapidly changing world in which we increasingly depend on the services our ecosystems  
47 provide, it is imperative that we are able to study and understand how ecological  
48 interactions change over space and time, which has traditionally relied on direct  
49 observations (Birkhofer et al., 2017; Symondson, 2002). Directly observing interactions is  
50 not always possible, but, when obtainable, it provides important and relatively  
51 unequivocal data. However, it is often laborious and constrained by observer biases and  
52 short timeframes, ultimately altering the networks of interactions constructed and our  
53 perception of the processes they drive (Cuff et al., 2022; Gibson et al., 2011). Sentinel  
54 approaches, whereby resources are placed in the environment to catalyse measurable  
55 processes, are a valuable method for studying ecological interactions in a semi-controlled  
56 way while reducing observer bias and field-based labour (Lövei & Ferrante, 2017). These  
57 resources can be artificial or present at artificial densities, but provide an important proxy  
58 for ecological interactions otherwise occurring in the focal environment (Kidd & Jervis,  
59 2007).

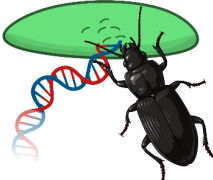

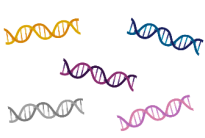
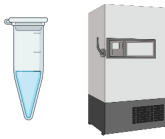


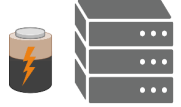


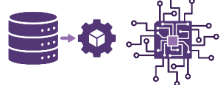
60 Ferrante and Lövei (2025) recently reviewed a broad range of sentinel methods which  
61 offer standardized, repeatable, and scalable ways to measure various ecosystem  
62 processes, such as predation, herbivory, decomposition, and pollination. These assays  
63 have become crucial tools for assessing ecosystem functioning, and broadening their use

64 beyond trophic interactions is incredibly promising, especially at scales incompatible with  
65 direct observation. While sentinel methods can quantify such processes as frequencies  
66 of visitation or consumption rates, they often fail to reveal precisely “who” performs the  
67 process or “how” the underlying interactions unfold. For example, seed trays or bite marks  
68 on clay caterpillars can determine the approximate frequency of consumption events, but  
69 say little about the species/agent behind the process being measured, when it interacted  
70 with the resource or its behaviour during or after the interaction (Lövei & Ferrante, 2017).  
71 Knowing if a process was executed by a native or invasive species, for example, could  
72 be crucial when studying the impact of invasive species on native fauna. How long the  
73 interaction takes and whether it happened during the day or night could similarly change  
74 how we understand and support ecological processes like pollination and the community  
75 of organisms that sustain them.

76 Alongside advances in the application of sentinel approaches, significant progress has  
77 been made in the broader remit of biomonitoring, enabling the remote detection of species  
78 and their interactions (Cuff, Deivarajan Suresh, et al., 2023; Derocles et al., 2018).  
79 Through the development and integration of established and emerging technologies such  
80 as high-throughput sequencing, computer vision and deep learning, the detection and  
81 identification of species and interactions has been streamlined, with clear progress toward  
82 in-field automation (Besson et al., 2022). Increasingly scalable and accessible DNA  
83 sequencing enables highly resolved identification of organisms from mere traces of their  
84 DNA left in the environment (Zhao & Andermann, 2026). Similarly, computer vision,  
85 especially through integration with deep learning, has enabled rapid and automated  
86 identification, counting and measurement of individuals from a range of image types

87 (Deivarajan Suresh et al., 2025; Ong et al., 2025). Despite the serendipity of these  
88 advances alongside those in broadening the remit of sentinel approaches, multimodal  
89 integration (i.e., using multiple detection modalities together) still remains scarce.

90 Integrating complementary technologies that reveal the “who”, “when” and “how” of  
91 interactions could transform sentinel studies from static measures of process intensity to  
92 tools capable of constructing wider ecological networks and their emergent properties  
93 such as ecosystem function. To achieve this, sentinel approaches will need to be coupled  
94 with technological tools which are capable of detecting taxa from biological traces or by  
95 directly recording behaviour (Figure 1). Two particularly promising prospects for  
96 integration are (i) trace environmental DNA (eDNA), which can be used to identify the  
97 taxa physically interacting with sentinel items through residual molecular traces, and (ii)  
98 camera traps paired with computer vision which can automate agent identification while  
99 documenting specific behaviours, timing, and frequency. Together, these complementary  
100 tools can expand sentinel methods into multimodal biomonitoring systems that determine  
101 the frequency of processes, the agents driving them and the functional consequences for  
102 wider ecosystems.

	Integrated method	Preparation	Exposure	Retrieval and analysis	Interpretation
Environmental DNA		 Sterilise materials	 Maximise DNA yield and integrity	 Stable and sterile sample storage	 Filter data to remove false positives
Computer vision		 Consider battery life, data storage and field degradation	 Deploy cameras discretely to avoid disturbance	 Backup data remotely or physically	 Consider deep learning and other automated data analysis cautiously

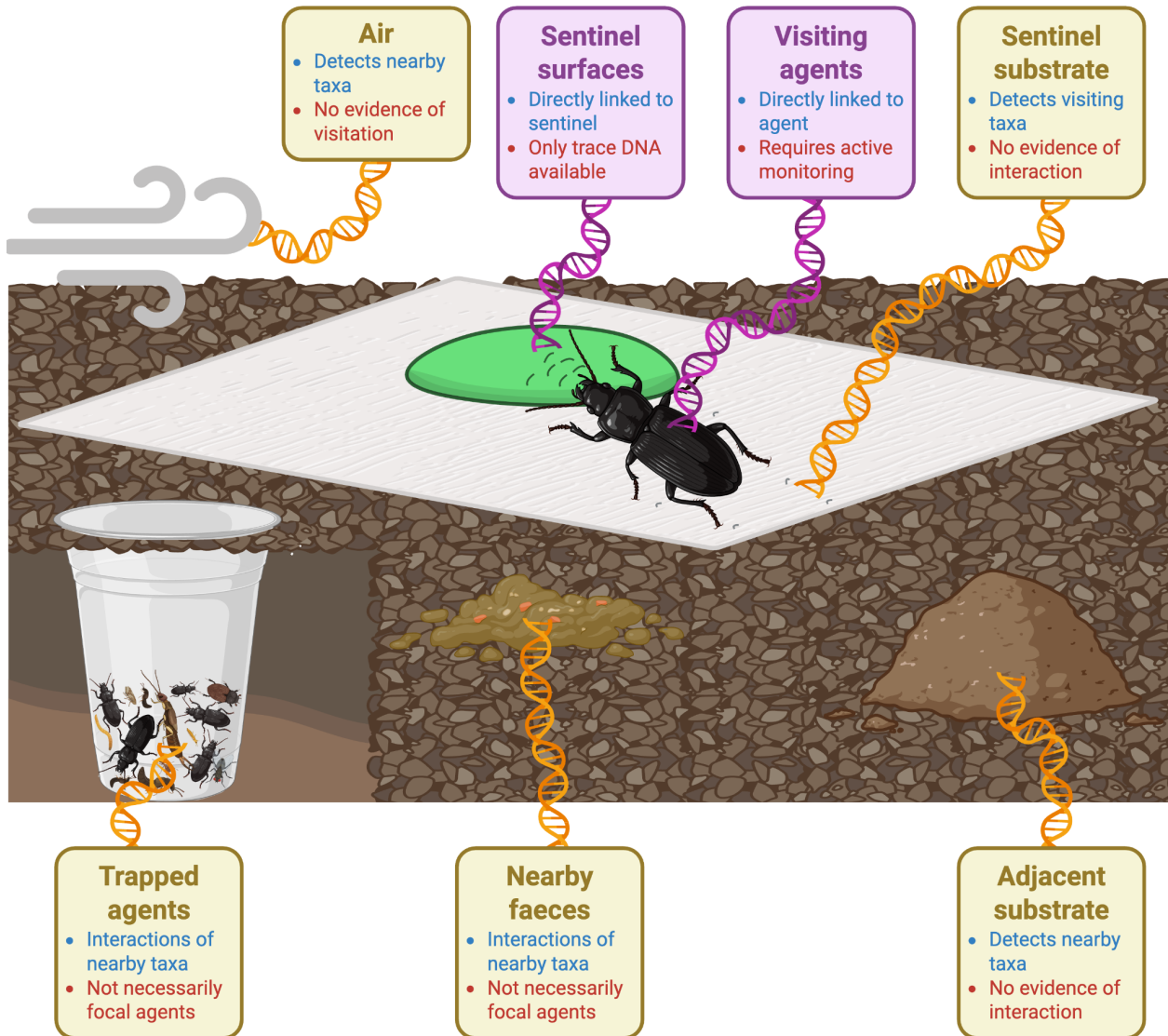
103  
104 Figure 1: An expansion of sentinel methods which uses multimodal integration of  
105 environmental DNA and computer vision for enhanced resolution, breadth and context.  
106 Each box represents considerations for the integration of these methods at each of the  
107 stages of the sentinel workflow. Created in BioRender. Cuff, J. (2026)  
108 <https://BioRender.com/viexxiy>  
109

110 **Environmental DNA as a tool for advancing sentinel**  
111 **approaches**

112 Identification of the agents interacting with sentinels has traditionally relied on coarse  
113 identification of cryptic evidence such as marks or damage patterns on sentinel objects  
114 (Lövei et al. 2017, Ferrante and Lövei 2025). Animals routinely leave DNA traces (e.g.,  
115 saliva, cells, hair) in the environment, including on natural (Lynggaard et al., 2023) or  
116 artificial (Kyle et al., 2022) surfaces. With appropriate care and diligence, these traces  
117 can be recovered and analysed using high-throughput sequencing methods like DNA  
118 metabarcoding to identify their source (Bohmann et al., 2014; Zhao & Andermann, 2026).  
119 This approach can often achieve species-level taxonomic resolution, enabling  
120 researchers to transcend the coarse identifications possible from marks on sentinel

121 objects (Rößler et al., 2018, 2020). There are various possible sources of this DNA  
 122 though, both direct and indirect, all of which could offer additional resolution to sentinel  
 123 approaches (Figure 2).

124



125  
 126 Figure 2: Sources of DNA that can be collected in parallel with the sentinel approach to  
 127 identify visiting agents or verify their interactions. Purple boxes denote direct analysis of  
 128 agents or sentinels, whereas yellow boxes denote indirect methods for identifying agents  
 129 or interactions. Blue text describes a benefit of each DNA source, whereas red text  
 130 indicates a key limitation of each. Created in BioRender. Cuff, J. (2026)  
 131 <https://BioRender.com/viexxiy>

132

133 Most intuitively, DNA could be removed from the sentinel objects that are interacted with  
134 (e.g., by swabbing DNA from sentinel surfaces) to detect and identify agents based on  
135 the DNA traces they leave behind (Rößler et al., 2020). This should accurately target the  
136 interacting agent, but the amount of DNA present on the sentinel may be variable and it  
137 may prove especially challenging when multiple species with disparate sizes or  
138 frequencies interact with the sentinel (i.e., the DNA of the smaller or less frequent visitor  
139 may be outcompeted). When using real resources, living or dead, as sentinels (e.g.,  
140 Gardarin et al., 2023; Seimandi-Corda et al., 2024; Zvereva & Kozlov, 2023) this  
141 approach would require exclusion of the DNA of the sentinel resource from analysis since  
142 it would otherwise likely comprise the majority of the data output (Cuff, Kitson, et al.,  
143 2023). While this is the most direct method of analysing the DNA of agent-sentinel  
144 interactions, other indirect methods warrant consideration.

145 If traps or other collection methods are deployed adjacent to sentinels (e.g., Gardarin et  
146 al. 2023), DNA could be taken from the surface, guts or faeces (depending on the focal  
147 taxon; Cohen et al., 2020; Cuff, Kitson, et al., 2023) of potential agents. If the agent is  
148 trapped adjacent to the sentinel, this may provide some confidence that it had interacted  
149 with the sentinel specifically, but, importantly, not certainty. This certainty could be  
150 increased if using a real sentinel resource not otherwise present in the system (e.g., a  
151 non-native species or taxon not usually found in that habitat), but this may detract from  
152 the ecological realism of the focal interactions which often results in criticism of sentinel  
153 methods. This will also only be effective if the sentinel itself contains DNA, as is the case  
154 for real prey attached to prey cards (e.g., Seimandi-Corda et al., 2024). For artificial

155 sentinels, synthetic DNA, which can be designed, synthesized and purchased from  
156 commercial manufacturers, could be impregnated in or on the sentinel material, similar to  
157 its use in laboratory positive controls for metabarcoding (Zinger et al., 2019). Degradation  
158 of that synthetic DNA in the environment and, subsequently, in the gut of the agent could,  
159 however, significantly hinder subsequent detection. Synthetic DNA would facilitate the  
160 parallel development and use of highly specific diagnostic assays that circumvent any  
161 need for relatively expensive sequencing though.

162 The substrate on which sentinels are placed can similarly be used for DNA analysis,  
163 whether that is a prey card on which sentinel prey are glued (e.g., Seimandi-Corda et al.,  
164 2024) or a natural substrate, such as soil, water or a plant. Environmental DNA can be  
165 recovered reliably from biotic and abiotic surfaces, including samples that confer direct  
166 evidence of consumption, such as faeces (Zhao & Andermann, 2026), all of which may  
167 be available at sentinel locations. To optimise DNA collection from approaching agents,  
168 the substrate on which the sentinel is placed could be lined with a material that enhances  
169 visual detection of their tracks (Kotler et al., 1993; Lettink et al., 2022). Similarly, hair  
170 sampling collars deployed near sentinels (Long et al., 2024) could provide DNA samples  
171 suitable for identification of the organisms approaching the sentinel. While visual  
172 inspection of footprints or hair can be inconclusive, much like bite marks on sentinels,  
173 DNA can be extracted directly from them to identify the agent with greater confidence and  
174 often to higher taxonomic resolutions (Hellström et al., 2023; Long et al., 2024). Leempoel  
175 et al. (2020), for example, demonstrated that DNA taken from the soil can represent many  
176 of the species detected by camera traps alongside various unique detections across the  
177 two methods. Similarly, airborne DNA can reveal spatially proximate taxa (Clare et al.,

178 2021), even when only passively sampled (Lin et al., 2025). Based on this principle, DNA  
179 extracted from sentinel-adjacent substrates could provide probable identities of visiting  
180 agents, and detection of taxa consistently across replicates would provide greater  
181 confidence in their importance to the focal ecological process. Moreover, genotyping  
182 approaches based on single nucleotide polymorphisms (SNPs) or whole genome  
183 sequencing could potentially allow estimation of the number of individual visitors to  
184 sentinels (Andres et al., 2023), which classical sentinels struggle to reveal. Having  
185 confidence in the accuracy of the data and identities provided by DNA integration would,  
186 however, benefit from additional evidence from other methods.

187 Before applying DNA-based analyses to sentinel approaches, it is important to consider  
188 context-dependent sources of error. Given the sensitivity of PCR-based DNA analyses  
189 like metabarcoding, susceptibility to false positives is high (Drake et al., 2022). To ensure  
190 accuracy, sources of those false positives, such as cross-contamination and  
191 environmental contaminants must be carefully controlled through use of field blanks (e.g.,  
192 sentinels that are inaccessible to target taxa) and sterile handling. Environmental factors  
193 that may contribute to DNA integrity, such as temperature, ultraviolet radiation and  
194 humidity, must also be considered since their impact on DNA persistence may introduce  
195 false negatives. Interpretation of the results also requires caution, even when taking DNA  
196 directly from sentinels, since DNA presence may indicate contact but not necessarily  
197 result from the process being studied (e.g., it may not reflect a predator attacking a prey  
198 sentinel). Alongside environmental contamination (e.g., from the air; Klepke et al., 2022),  
199 agents themselves may introduce contaminants or other false positives (e.g., DNA from  
200 the agent's previous meal; Rößler et al., 2020). Special consideration is therefore required

201 in experimental design for the field but also for establishing rigorous laboratory workflows,  
202 bioinformatics processes and data filtration (Alberdi et al., 2019; Drake et al., 2022). The  
203 lack of reliable quantitative data (Deagle et al., 2019; Lamb et al., 2019) and important  
204 context such as the life stage of the agents (Cuff et al., 2022, 2026) that these data  
205 provide, alongside conceptual problems like pervasive taxonomic biases (Alberdi et al.,  
206 2019; Piñol et al., 2019), leave several key gaps. Despite these caveats, DNA-based  
207 analyses are increasingly widely adopted and can provide an unprecedented taxonomic  
208 resolution to sentinel methods to gain a richer understanding of ecological processes.

209

## 210 **Cameras and computer vision to identify agents and their** 211 **behaviour**

212 Given that they are usually stationary in a known location, sentinels are, by design,  
213 relatively easy to observe. This makes their integration with camera trapping relatively  
214 straightforward and increasingly commonplace. Camera traps can complement sentinel  
215 studies by providing visual and behavioural observations of interactions (Smith et al.,  
216 2020) even for small-bodied organisms, such as invertebrates (Gardarin et al., 2023;  
217 Nagy et al., 2020; Seimandi-Corda et al., 2025). When positioned near sentinel items,  
218 they can record the species visiting, when it visits and what they do (Smith et al., 2020).  
219 This could delineate between behaviours like inspection, attack or avoidance, for  
220 example, or even identify interactions aborted due to barriers like interference  
221 competition. Cameras can also clarify a phenomenon that often occurs in sentinel  
222 experiments, where sentinels disappear or are depleted (Lövei & Ferrante, 2017), with

223 significant implications for interpretation of interaction frequencies. They can also provide  
224 valuable information on an agent's life stage, activity patterns, temporal niche and overlap  
225 with natural resource timing (Gardarin et al., 2023; Nagy et al., 2020; Seimandi-Corda et  
226 al., 2024; Smith et al., 2020; Zvereva & Kozlov, 2023).

227 While camera traps are powerful monitoring tools, processing their images can require  
228 many hours of manual screening (Seimandi-Corda et al., 2024). Recent advances in deep  
229 learning and computer vision now facilitate the automatic processing of large image  
230 datasets, identifying species or morphogroups and the frequencies of specific behaviours  
231 at unprecedented scales (Seimandi-Corda et al., 2025; Vélez et al., 2023). This approach  
232 has been successfully applied to camera trap images (Bjerge et al., 2023), and models  
233 trained on relevant datasets can classify a broad array of taxa, even tracking animals in  
234 real-time (Bjerge et al., 2022). With appropriate reference or training data, it will also be  
235 possible to automate the detection and tracking of specific ecological interactions,  
236 including interaction with a sentinel resource. Delegating image processing to artificial  
237 intelligence systems must be done cautiously and with careful validation, while  
238 acknowledging that species-level identification is not always accurate nor achievable  
239 (Alison et al., 2026). Sittinger et al. (2024) demonstrated the use of InsectDetect cameras  
240 alongside artificial sentinel flowers, enabling simultaneous measurement of interaction  
241 rates and taxonomic identities of visiting agents to construct detailed pollinator networks.  
242 Insect camera traps can be paired with artificial 3D printed flowers to standardise and  
243 improve pollinator attraction (Ash et al., 2026). Cameras can also capture the  
244 environmental context that such interactions occur in, either through auxiliary sensors

245 (commonly integrated in trail cameras) or through analysis of the images captured (Alison  
246 et al., 2024).

247 In addition to detection and identification of interactions during sentinel deployment,  
248 computer vision and deep learning could advance the current practice of identifying  
249 agents from marks left on sentinel resources. These marks, left, for example, by the  
250 mouthparts of a predator on a sentinel prey, are often difficult to identify with precision  
251 given the minute differences between taxa. Such differences could, theoretically, be  
252 distinguished by deep learning from sentinels imaged after a full round of deployment if  
253 sufficiently high-quality reference data (e.g., generated in controlled laboratory  
254 experiments; Ferrante et al., 2024) was available for different taxa. One of the greatest  
255 challenges in applying deep learning to such problems is the standardisation of image  
256 resolution, lighting and angling. Charged coupled device flatbed scanners have been  
257 demonstrably successful in overcoming this problem for other material types, such as  
258 insect sticky traps (Deivarajan Suresh et al., 2025; Ong et al., 2025), and could similarly  
259 standardise images of sentinel prey marks for deep learning-based identification. This  
260 approach can help reduce the subjectivity inherent in interpreting marks on sentinels,  
261 which is a known limitation in classical sentinel studies (Valdés-Correcher et al., 2022),  
262 while also providing standardised reference material for developing tools to train new  
263 observers. It could be further expanded through 3D scanning of sentinel objects,  
264 generating more detailed and standardised representations of attack marks (Naether et  
265 al., 2012). Such representations may even offer additional information about the  
266 interacting agent, including, for example, bite mark dimensions to compare against  
267 recorded morphology/size (Young et al., 2015). Which can be used for inference of the

268 biomechanical constraints of interactions (Cuff, Labonte, et al., 2024; Püffel et al., 2023).  
269 Sentinel units could be efficiently scanned at scale by mounting them on labeled pins with  
270 individual identification codes.

271 Camera trapping can help overcome some subjectivity in sentinel approaches, but some  
272 studies suggest that they are better suited to capturing activity patterns rather than actual  
273 processes or interactions like predation (Schillé et al., 2025). Designing sentinels that  
274 require prolonged interaction time and advances in the equipment available for camera  
275 trapping may address this through the provision of more continuous and dynamic data  
276 (Schillé et al., 2026) but this nevertheless demonstrates the importance of validation with  
277 other data types. The potential mismatch between activity and predation could, if  
278 determined through cross-validation, help to address whether artificial sentinel prey are  
279 sufficiently attractive. By detecting organisms that approach but do not interact with the  
280 sentinel (Gardarin et al., 2023; Nagy et al., 2020; Schillé et al., 2026), camera data could  
281 help to address concerns that sentinel methods do not mimic natural processes and may  
282 distort our inference of the relative importance of different taxonomic groups (Nagy et al.,  
283 2020; Schillé et al., 2026; Zvereva et al., 2024; Zvereva & Kozlov, 2023). Sentinels could  
284 be refined stepwise to reduce hesitation or non-interaction based on such data; for  
285 example, if a predator, such as a bird, was found to approach but never attack a clay  
286 caterpillar, it may indicate that it too poorly mimics an actual caterpillar. Naïve juvenile  
287 birds, for example, may be more likely to attack artificial caterpillars than their adult  
288 counterparts (Zvereva & Kozlov, 2023). Refining sentinels based on these data could  
289 enhance their capacity to measure the processes they aim to quantify reliably (Lövei &  
290 Ferrante, 2017; Schillé et al., 2025).

291 Several challenges will remain pervasive in applying this approach though, such as  
292 classification uncertainty, reduced performance under low light, occlusion, limited training  
293 images or model performance (Alison et al., 2026; Seimandi-Corda et al., 2025). The  
294 potential of automated cameras to capture fine-scale temporal and behavioural data  
295 nevertheless makes them an obvious and powerful extension to sentinel experiments.  
296 The resolution of the images captured can often taxonomically limit identifications though  
297 (Nagy et al., 2020), especially when using the more cost-effective setups necessary when  
298 monitoring at scale. This issue of low resolution could be addressed through multimodal  
299 integration.

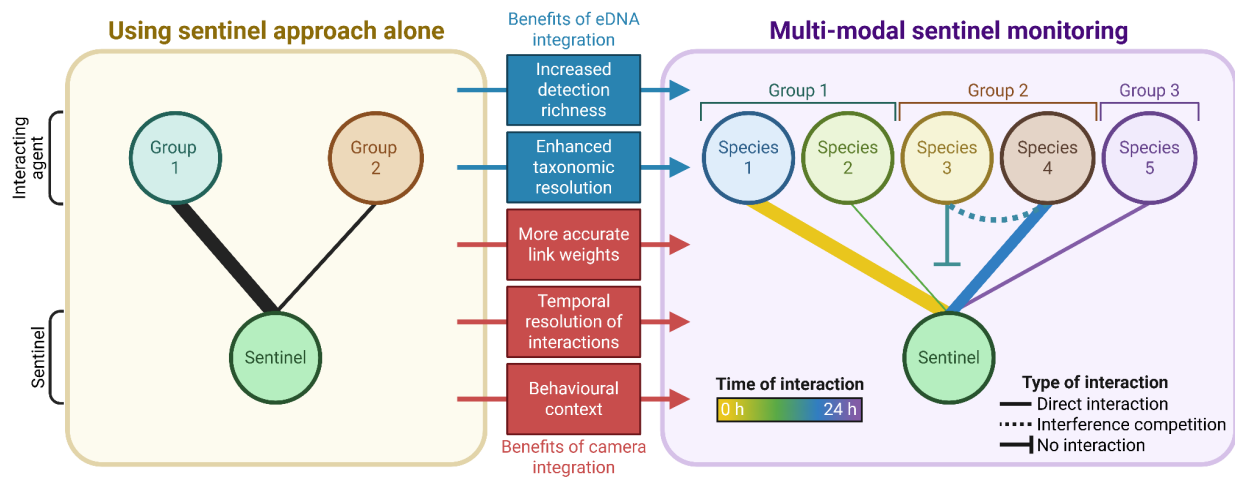
300

## 301 **Multimodal integration with sentinel approaches**

302 Given the inherent biases of individual sampling methods used in monitoring and  
303 research, attention has increasingly turned toward the integration of methods. This  
304 merged or multimodal monitoring is central to the premise of 'next generation  
305 biomonitoring' which aims to enhance the resolution and scale of monitoring through  
306 integration of emerging technologies for the generation of meaningful metrics to assess  
307 ecosystem health (Besson et al., 2022; Cuff, Deivarajan Suresh, et al., 2023; Derocles et  
308 al., 2018). The rationale for merging methods is that different datasets offer opportunities  
309 for cross-validation, complementary detections and complementary data types, all of  
310 which contribute to more complete and accurate data (Zipkin et al., 2021). In the context  
311 of ecological networks, which the sentinel approach can be used to construct, this can  
312 have important implications for the structural properties of networks and the outcomes of

313 network analyses (Cuff, Deivarajan Suresh, et al., 2023; Windsor, 2023; Figure 3).  
 314 Illustrating the value of integrating methods, Leempoel et al. (2020) and Kakita et al.  
 315 (2026) separately showed that parallel analysis of camera trap images and DNA taken  
 316 from the soil adjacent to the cameras resulted in overlapping but complementary  
 317 detections. This naturally overlaps conceptually with the application of camera trapping  
 318 and DNA-based analysis to sentinels, which would likely result in similarly complementary  
 319 detections.

320



321  
 322 Figure 3: By using multimodal data to identify, quantify and characterise processes linked  
 323 to sentinels, the interaction data generated will be much more resolved than if using the  
 324 sentinel approach alone. Analysing environmental DNA from sentinels, adjacent surfaces  
 325 or potential agents may increase the known richness of agents interacting with the  
 326 sentinel through both increased sensitivity and enhanced taxonomic resolution. The use  
 327 of cameras alongside sentinels may enhance contextual data by improving quantification  
 328 of link weights, the temporal resolution of interaction data and the behavioural context of  
 329 the interactions (including non-interacting taxa and those displaying interference  
 330 competition). Taken together, a multimodal sentinel approach may result in a much more  
 331 detailed and realistic understanding of sentinel-agent interactions. Created in BioRender.  
 332 Cuff, J. (2026) <https://BioRender.com/viexxiy>

333

334 The integration of different data types could significantly extend the potential applications  
335 and outcomes of sentinel studies (Figure 3). As detailed above, DNA data can provide  
336 significant advances to taxon resolution, whereas image-based analysis can provide  
337 context-rich data pertaining to specific behaviours or agent states (e.g., life stage;  
338 Seimandi-Corda et al., 2024). Their integration generates a rich dataset through which  
339 variation in interaction frequency, identity and function can be explored more fully than by  
340 either method in isolation. This complementarity of data types does, however, present  
341 some distinct challenges. The pitfalls of data merging have been summarised elsewhere  
342 (e.g., Cuff, Deivarajan Suresh, et al., 2023; Cuff et al., 2022; Zipkin et al., 2021), but  
343 include differences in the units of measurement, quantitative vs. qualitative, taxonomic  
344 resolutions, spatiotemporal scales, completeness, biases and sampling  
345 perspectives/orientation. Data handling processes like per-sample normalisation or  
346 reduction to frequencies of occurrence can overcome some of these challenges, but at  
347 the expense of ecological realism (Cuff, Terrel, et al., 2024). The expense and complexity  
348 of running multiple methods in parallel is also noteworthy given the financial cost of  
349 processes like high-throughput sequencing and equipment like high resolution field-  
350 deployable cameras (Alison et al., 2026). Consequently, whether and how multimodal  
351 data collection should be integrated depends on the ecological processes of interest and  
352 the goals of the study.

353

## 354 **When to integrate sentinel approaches with other monitoring** 355 **methods**

356 Classic sentinel assays remain ideal for rapid and straightforward standardised  
357 comparisons of ecological process rates across space, time or treatments, particularly  
358 when questions focus on magnitude rather than mechanism or identity. When the  
359 ecological question requires identification of the species driving the process, behavioural  
360 context or temporal resolution for accurate interpretation, integrating molecular and  
361 image-based monitoring may become essential. Environmental DNA is useful when  
362 substantial physical contact with the sentinel object is expected and the taxonomic identity  
363 of the agent is important (Rößler et al., 2020; Shaw et al., 2023). Meanwhile, cameras  
364 can record both interacting and non-interacting visitors, offering behavioural context and  
365 fine temporal resolution (Nagy et al., 2020; Schillé et al., 2026). Choosing between, or  
366 combining, these tools should be guided by the ecological question, available resources  
367 and logistical feasibility.

368 The additional complexity and data management demands of multimodal sentinels are  
369 justified when they provide mechanistic insight that traditional approaches cannot. A  
370 hybrid framework, in which classical sentinels quantify process rates and a subset of  
371 enhanced sentinels with multimodal integration reveal the responsible agents and their  
372 behaviours could allow researchers to balance depth, cost and scalability. Samples (e.g.,  
373 whole sentinels, swabs, other materials) could be collected and stored appropriately for  
374 later use of DNA-based analyses without committing finance or labour, but this does  
375 require specific storage conditions and procedures to limit contamination. Collecting  
376 samples and storing them via deep freezing can effectively preserve DNA for analysis,  
377 allowing those samples to be processed only when needed, even far into the future. When  
378 funding is limited, camera-based approaches may be especially suitable because the

379 equipment can be reused across multiple studies and projects involving sentinels,  
380 whereas eDNA workflows often require recurring consumable costs.

381 Expanding sentinel methods with complementary approaches such as eDNA or cameras  
382 should not be an objective in itself. These integrations demand additional time, expertise,  
383 and resources, and should therefore only be pursued when the added value justifies the  
384 additional effort and cost. Ideally, such expansions would be guided by a clearly defined  
385 ecological question or hypothesis that cannot be adequately addressed through classical  
386 sentinel assays alone. For instance, one might ask whether multiple species share the  
387 same ecological role or if a single taxon dominates a process (i.e., functional  
388 redundancy), which may be addressed through integration of eDNA and cameras.  
389 Similarly, this approach can assess whether targeted management schemes are focusing  
390 on the most beneficial taxa and can optimise management therein. For augmentative  
391 releases of biocontrol agents, for example, knowing whether specific agents are exerting  
392 predation pressure and whether this aligns with the diel cycles of the target pests is  
393 essential, and could be informed by camera deployment (e.g., Seimandi-Corda et al.,  
394 2024). Beyond hypothesis-driven integrations, it is important to note that collecting richer  
395 datasets exploratively can sometimes reveal unexpected patterns and generate new  
396 hypotheses. While we recommend prioritising hypothesis-led integration of multimodal  
397 sentinel studies, and we encourage a clear rationale for expanding the method, there is  
398 an important place for exploratory integration too, especially when developing new  
399 methodological approaches.

400

## 401 **Conclusions**

402 Sentinel approaches provide opportunities to expose and compare ecological processes  
403 experimentally under controlled and repeatable conditions. These systems offer an ideal  
404 platform for integrating complementary data modalities that link ecological processes with  
405 the organisms and behaviours that drive them. When applied selectively and guided by  
406 clear ecological questions, such integrations can move sentinel studies toward a deeper  
407 mechanistic understanding of ecological interactions and ecosystem functioning.

408 While we have focused here on the potential integration of DNA-based analysis and  
409 camera trapping with sentinels, there are various other methodological modalities that  
410 could introduce complementary data. Bioacoustics, for example, could provide data on  
411 the community of potential agents (Schillé et al., 2026), the duration of resource handling  
412 (Stidsholt et al., 2025) or even the uncharted complexity of sentinel-agent interaction  
413 networks (Dawson et al., 2026). Given the importance of volatile organic compounds in  
414 communication, they could be analysed at sentinel stations to generate data such as the  
415 disease status of agents (Asiri et al., 2024). Alongside the integration of additional  
416 modalities, the framework presented in this article could be promising for integration with  
417 different types of sentinels focused on physiological outcomes. Experiments typically  
418 conducted with baits, such as nutrient choice experiments in natural environments (e.g.,  
419 Guariento et al., 2021) could be monitored more precisely than has traditionally been  
420 possible if conducted in this multimodal framework. Multimodal integration can facilitate  
421 continued advances to sentinel approaches for an increasingly accurate and valuable

422 source of ecological interaction data. We hope this perspective encourages further  
423 development and testing of multimodal sentinel approaches across sentinel systems.

424

## 425 **Author contributions**

426 Yuval Cohen: Conceptualization; visualisation; writing – original draft; writing - review and  
427 editing. Jordan P. Cuff: Conceptualization; visualisation; writing – original draft; writing -  
428 review and editing. Liora Shaltiel-Harpaz: writing - review and editing.

429

## 430 **Acknowledgments**

431 JPC was funded by a Newcastle University Academic Track Fellowship. For the purpose  
432 of open access, the author has applied a Creative Commons Attribution (CC BY) licence  
433 to any Author Accepted Manuscript version arising from this submission. This publication  
434 is based upon work from COST Action InsectAI (CA22129), supported by COST  
435 (European Cooperation in Science and Technology).

436

## 437 **Data availability**

438 No data was generated or used for this manuscript.

439

## 440 **References**

441 Alberdi, A., Aizpurua, O., Bohmann, K., Gopalakrishnan, S., Lynggaard, C., Nielsen, M., &  
442 Gilbert, M. T. P. (2019). Promises and pitfalls of using high-throughput sequencing for  
443 diet analysis. *Molecular Ecology Resources*, 19(2), 327–348.  
444 <https://doi.org/10.1111/1755-0998.12960>

445 Alison, J., Payne, S., Alexander, J. M., Bjorkman, A. D., Clark, V. R., Gwate, O., Huntsaar, M.,  
446 Iseli, E., Lenoir, J., Mann, H. M. R., Steenhuisen, S., & Høye, T. T. (2024). Deep  
447 learning to extract the meteorological by-catch of wildlife cameras. *Global Change*  
448 *Biology*, 30(1), e17078. <https://doi.org/10.1111/gcb.17078>

449 Alison, J., Pegoraro, L., Blair, J., Cohen, Y., Haest, B., Idec, J., Kamminga, J., Lawson, J., Li,  
450 M., Do Nascimento, L., Outhwaite, C., Rutschmann, B., Sittinger, M., Abarca, M.,  
451 August, T., Geissmann, Q., Guralnick, R., Mougeot, G., Ştefan, V., ... Van Klink, R.  
452 (2026). *Insect monitoring without pitfalls: Seven steps for robust insect sensing systems*.  
453 <https://doi.org/10.32942/X2MD4V>

454 Andres, K. J., Lodge, D. M., Sethi, S. A., & Andrés, J. (2023). Detecting and analysing  
455 intraspecific genetic variation with EDNA: From population genetics to species  
456 abundance. *Molecular Ecology*, 32(15), 4118–4132. <https://doi.org/10.1111/mec.17031>

457 Ash, A., Hallett, S., Carvell, C., Williams, L., & August, T. (2026). *Testing the efficacy of artificial*  
458 *flowers as a novel attractant for automated pollinator monitoring*.  
459 <https://doi.org/10.64898/2026.01.23.698111>

460 Asiri, A., Perkins, S. E., & Müller, C. T. (2024). The smell of infection: Disease surveillance in  
461 insects using volatile organic compounds. *Agricultural and Forest Entomology*,  
462 afe.12651. <https://doi.org/10.1111/afe.12651>

463 Besson, M., Alison, J., Bjerge, K., Goroehowski, T. E., Høye, T. T., Jucker, T., Mann, H. M. R.,  
464 & Clements, C. F. (2022). Towards the fully automated monitoring of ecological  
465 communities. *Ecology Letters*, 25(12), 2753–2775. <https://doi.org/10.1111/ele.14123>

466 Birkhofer, K., Bylund, H., Dalin, P., Ferlian, O., Gagic, V., Hambäck, P. A., Klapwijk, M., Mestre,  
467 L., Roubinet, E., Schroeder, M., Stenberg, J. A., Porcel, M., Björkman, C., & Jonsson, M.  
468 (2017). Methods to identify the prey of invertebrate predators in terrestrial field studies.  
469 *Ecology and Evolution*, 7(6), 1942–1953. <https://doi.org/10.1002/ece3.2791>

470 Bjerger, K., Alison, J., Dyrmann, M., Frigaard, C. E., Mann, H. M. R., & Høye, T. T. (2023).  
471 Accurate detection and identification of insects from camera trap images with deep  
472 learning. *PLOS Sustainability and Transformation*, 2(3), e0000051.  
473 <https://doi.org/10.1371/journal.pstr.0000051>

474 Bjerger, K., Mann, H. M. R., & Høye, T. T. (2022). Real-time insect tracking and monitoring with  
475 computer vision and deep learning. *Remote Sensing in Ecology and Conservation*, 8(3),  
476 315–327. <https://doi.org/10.1002/rse2.245>

477 Bohmann, K., Evans, A., Gilbert, M. T. P., Carvalho, G. R., Creer, S., Knapp, M., Yu, D. W., &  
478 De Bruyn, M. (2014). Environmental DNA for wildlife biology and biodiversity monitoring.  
479 *Trends in Ecology & Evolution*, 29(6), 358–367.  
480 <https://doi.org/10.1016/j.tree.2014.04.003>

481 Clare, E. L., Economou, C. K., Faulkes, C. G., Gilbert, J. D., Bennett, F., Drinkwater, R., &  
482 Littlefair, J. E. (2021). eDNAir: Proof of concept that animal DNA can be collected from  
483 air sampling. *PeerJ*, 9, e11030. <https://doi.org/10.7717/peerj.11030>

484 Cohen, Y., Bar-David, S., Nielsen, M., Bohmann, K., & Korine, C. (2020). An appetite for pests:  
485 Synanthropic insectivorous bats exploit cotton pest irruptions and consume various  
486 deleterious arthropods. *Molecular Ecology*, 29(6), 1185–1198.  
487 <https://doi.org/10.1111/mec.15393>

488 Cuff, J. P., Deivarajan Suresh, M., Dopson, M. E. G., Hawthorne, B. S. J., Howells, T., Kitson, J.  
489 J. N., Miller, K. A., Xin, T., & Evans, D. M. (2023). A roadmap for biomonitoring in the  
490 21st century: Merging methods into metrics via ecological networks. *Advances in*  
491 *Ecological Research*, 68, 1–34. <https://doi.org/10.1016/bs.aecr.2023.09.002>

492 Cuff, J. P., Kitson, J. J. N., Hemprich-Bennett, D., Tercel, M. P. T. G., Browett, S. S., & Evans,  
493 D. M. (2023). The predator problem and PCR primers in molecular dietary analysis:  
494 Swamped or silenced; depth or breadth? *Molecular Ecology Resources*, 23(1), 41–51.  
495 <https://doi.org/10.1111/1755-0998.13705>

496 Cuff, J. P., Kitson, J. J. N., Windsor, F. M., Sint, D., Hawthorne, B. S. J., Traugott, M., Anderson,  
497 C. M. H., Neidel, V., Gatehouse, A. M. R., Thwaites, D. T., Edwards, M. G., & Evans, D.  
498 (2026). Dietary RNA: Diagnostic and functional RNA offer a potential paradigm shift for  
499 molecular dietary analyses. *Molecular Ecology Resources*, in press.  
500 <https://doi.org/10.1111/1755-0998.70139>

501 Cuff, J. P., Labonte, D., & Windsor, F. M. (2024). Understanding Trophic Interactions in a  
502 Warming World by Bridging Foraging Ecology and Biomechanics with Network Science.  
503 *Integrative And Comparative Biology*, 64(2), 306–321.  
504 <https://doi.org/10.1093/icb/icae070>

505 Cuff, J. P., Tercel, M. P. T. G., Windsor, F. M., Hawthorne, B. S. J., Hambäck, P. A., Bell, J. R.,  
506 Symondson, W. O. C., & Vaughan, I. P. (2024). Sources of prey availability data alter  
507 interpretation of outputs from prey choice null networks. *Ecological Entomology*, 49(3),  
508 418–432. <https://doi.org/10.1111/een.13315>

509 Cuff, J. P., Windsor, F. M., Tercel, M. P. T. G., Kitson, J. J. N., & Evans, D. M. (2022).  
510 Overcoming the pitfalls of merging dietary metabarcoding into ecological networks.  
511 *Methods in Ecology and Evolution*, 13(3), 545–559. [https://doi.org/10.1111/2041-](https://doi.org/10.1111/2041-210X.13796)  
512 [210X.13796](https://doi.org/10.1111/2041-210X.13796)

513 Dawson, W., Evans, D. M., Abrahams, C., Kitson, J. J. N., Collins, L., & Cuff, J. P. (2026).  
514 Ecoacoustics for context-rich direct and indirect trophic interaction data and ecological  
515 network construction. *Methods in Ecology and Evolution*, 2041-210x.70288.  
516 <https://doi.org/10.1111/2041-210x.70288>

517 Deagle, B. E., Thomas, A. C., McInnes, J. C., Clarke, L. J., Vesterinen, E. J., Clare, E. L.,  
518 Kartzinel, T. R., & Eveson, J. P. (2019). Counting with DNA in metabarcoding studies:  
519 How should we convert sequence reads to dietary data? *Molecular Ecology*, *28*(2), 391–  
520 406. <https://doi.org/10.1111/mec.14734>

521 Deivarajan Suresh, M., Xin, T., Cook, S. M., & Evans, D. M. (2025). Bugs and bytes:  
522 Entomological biomonitoring through the integration of deep learning and molecular  
523 analysis for merged community and network analysis. *Agricultural and Forest*  
524 *Entomology*, *27*(1), 35–49. <https://doi.org/10.1111/afe.12667>

525 Derocles, S. A. P., Bohan, D. A., Dumbrell, A. J., Kitson, J. J. N., Massol, F., Pauvert, C.,  
526 Plantegenest, M., Vacher, C., & Evans, D. M. (2018). Biomonitoring for the 21st Century:  
527 Integrating Next-Generation Sequencing Into Ecological Network Analysis. In *Advances*  
528 *in Ecological Research* (Vol. 58, pp. 1–62). Elsevier.  
529 <https://doi.org/10.1016/bs.aecr.2017.12.001>

530 Drake, L. E., Cuff, J. P., Young, R. E., Marchbank, A., Chadwick, E. A., & Symondson, W. O. C.  
531 (2022). An assessment of minimum sequence copy thresholds for identifying and  
532 reducing the prevalence of artefacts in dietary metabarcoding data. *Methods in Ecology*  
533 *and Evolution*, *13*(3), 694–710. <https://doi.org/10.1111/2041-210X.13780>

534 Ferrante, M., Howe, A. G., & Lövei, G. L. (2024). Experimental considerations support the use  
535 of artificial sentinel prey—A comment on Rodriguez-Campbell et al. *Journal of*  
536 *Biogeography*, *51*(11), 2152–2155. <https://doi.org/10.1111/jbi.14978>

537 Ferrante, M., & Lövei, G. L. (2025). The sentinel approach to quantify ecosystem function  
538 intensities. *Methods in Ecology and Evolution*, *16*(10), 2305–2317.  
539 <https://doi.org/10.1111/2041-210X.70143>

540 Gardarin, A., Capowiez, Y., Teulé, J.-M., Wetzels, G., & Hedde, M. (2023). Assessing ground  
541 predation by invertebrates in crops: Camera observations clarify the relevance of aphid

542 cards and coleopteran sentinel prey. *Basic and Applied Ecology*, 71, 111–118.  
543 <https://doi.org/10.1016/j.baae.2023.07.002>

544 Gibson, R. H., Knott, B., Eberlein, T., & Memmott, J. (2011). Sampling method influences the  
545 structure of plant–pollinator networks. *Oikos*, 120(6), 822–831.  
546 <https://doi.org/10.1111/j.1600-0706.2010.18927.x>

547 Guariento, E., Wanek, W., & Fiedler, K. (2021). Consistent shift in nutritional ecology of ants  
548 reveals trophic flexibility across alpine tree-line ecotones. *Ecological Entomology*, 46(5),  
549 1082–1092. <https://doi.org/10.1111/een.13052>

550 Hellström, M., Kruger, E., Näslund, J., Bisther, M., Edlund, A., Hernvall, P., Birgersson, V.,  
551 Augusto, R., & Lancaster, M. L. (2023). Capturing environmental DNA in snow tracks of  
552 polar bear, Eurasian lynx and snow leopard towards individual identification. *Frontiers in*  
553 *Conservation Science*, 4, 1250996. <https://doi.org/10.3389/fcosc.2023.1250996>

554 Kakita, M., Furuta, Y., & Tanaka, H. (2026). A Ground Surface Rolling Method for Detecting  
555 Environmental DNA of Terrestrial Animals. *Environmental DNA*, 8(1), e70248.  
556 <https://doi.org/10.1002/edn3.70248>

557 Kidd, N. A. C., & Jervis, M. A. (2007). Population Dynamics. In M. A. Jervis (Ed.), *Insects As*  
558 *Natural Enemies* (pp. 435–523). Springer Netherlands. [https://doi.org/10.1007/978-1-](https://doi.org/10.1007/978-1-4020-2625-6_7)  
559 [4020-2625-6\\_7](https://doi.org/10.1007/978-1-4020-2625-6_7)

560 Klepke, M. J., Sigsgaard, E. E., Jensen, M. R., Olsen, K., & Thomsen, P. F. (2022).  
561 Accumulation and diversity of airborne, eukaryotic environmental DNA. *Environmental*  
562 *DNA*, 4(6), 1323–1339. <https://doi.org/10.1002/edn3.340>

563 Kotler, B. P., Brown, J. S., & Mitchell, W. A. (1993). Environmental Factors Affecting Patch use  
564 in two Species of Gerbilline Rodents. *Journal of Mammalogy*, 74(3), 614–620.  
565 <https://doi.org/10.2307/1382281>

566 Kyle, K. E., Allen, M. C., Dragon, J., Bunnell, J. F., Reinert, H. K., Zappalorti, R., Jaffe, B. D.,  
567 Angle, J. C., & Lockwood, J. L. (2022). Combining surface and soil environmental DNA

568 with artificial cover objects to improve terrestrial reptile survey detection. *Conservation*  
569 *Biology*, 36(6), e13939. <https://doi.org/10.1111/cobi.13939>

570 Lamb, P. D., Hunter, E., Pinnegar, J. K., Creer, S., Davies, R. G., & Taylor, M. I. (2019). How  
571 quantitative is metabarcoding: A meta-analytical approach. *Molecular Ecology*, 28(2),  
572 420–430. <https://doi.org/10.1111/mec.14920>

573 Leempoel, K., Hebert, T., & Hadly, E. A. (2020). A comparison of eDNA to camera trapping for  
574 assessment of terrestrial mammal diversity. *Proceedings of the Royal Society B:*  
575 *Biological Sciences*, 287(1918), 20192353. <https://doi.org/10.1098/rspb.2019.2353>

576 Lettink, M., Young, J., & Monks, J. M. (2022). Comparison of footprint tracking and pitfall  
577 trapping for detecting skinks. *New Zealand Journal of Ecology*, 46(2), 1–5.

578 Lin, R., Yan, Z., & Yao, M. (2025). Robust passive sampling of airborne environmental DNA to  
579 monitor plants and animals. *Methods in Ecology and Evolution*, 16(9), 2118–2130.  
580 <https://doi.org/10.1111/2041-210X.70102>

581 Long, R. A., MacKay, P., Sauder, J. D., Sinclair, M., Aubry, K. B., & Raley, C. M. (2024). An  
582 overwinter protocol for detecting wolverines and other carnivores at camera traps paired  
583 with automated scent dispensers. *Ecology and Evolution*, 14(5), e11290.  
584 <https://doi.org/10.1002/ece3.11290>

585 Lövei, G. L., & Ferrante, M. (2017). A review of the sentinel prey method as a way of quantifying  
586 invertebrate predation under field conditions. *Insect Science*, 24(4), 528–542.  
587 <https://doi.org/10.1111/1744-7917.12405>

588 Lynggaard, C., Calvignac-Spencer, S., Chapman, C. A., Kalbitzer, U., Leendertz, F. H., Omeja,  
589 P. A., Opito, E. A., Sarkar, D., Bohmann, K., & Gogarten, J. F. (2023). Vertebrate  
590 environmental DNA from leaf swabs. *Current Biology*, 33(16), R853–R854.  
591 <https://doi.org/10.1016/j.cub.2023.06.031>

592 Naether, S., Buck, U., Campana, L., Breitbeck, R., & Thali, M. (2012). The examination and  
593 identification of bite marks in foods using 3D scanning and 3D comparison methods.

594 *International Journal of Legal Medicine*, 126(1), 89–95. <https://doi.org/10.1007/s00414->  
595 011-0580-7

596 Nagy, R. K., Schellhorn, N. A., & Zalucki, M. P. (2020). Fresh, frozen or fake: A comparison of  
597 predation rates measured by various types of sentinel prey. *Journal of Applied*  
598 *Entomology*, 144(5), 407–416. <https://doi.org/10.1111/jen.12745>

599 Ong, S.-Q., Pinoy, N., Lim, M. H., Bjerge, K., Peris-Felipo, F. J., Lind, R., Cuff, J. P., Cook, S.  
600 M., & Høye, T. T. (2025). ScannerVision: Scanner-based image acquisition of medically  
601 important arthropods for the development of computer vision and deep learning models.  
602 *Current Research in Parasitology & Vector-Borne Diseases*, in press.

603 Piñol, J., Senar, M. A., & Symondson, W. O. C. (2019). The choice of universal primers and the  
604 characteristics of the species mixture determine when DNA metabarcoding can be  
605 quantitative. *Molecular Ecology*, 28(2), 407–419. <https://doi.org/10.1111/mec.14776>

606 Püffel, F., Roces, F., & Labonte, D. (2023). Strong positive allometry of bite force in leaf-cutter  
607 ants increases the range of cuttable plant tissues. *Journal of Experimental Biology*,  
608 jeb.245140. <https://doi.org/10.1242/jeb.245140>

609 Rößler, D. C., Lötters, S., Veith, M., Fugmann, M., Peters, C., Künzel, S., & Krehenwinkel, H.  
610 (2020). An amplicon sequencing protocol for attacker identification from DNA traces left  
611 on artificial prey. *Methods in Ecology and Evolution*, 11(10), 1338–1347.  
612 <https://doi.org/10.1111/2041-210X.13459>

613 Rößler, D. C., Pröhl, H., & Lötters, S. (2018). The future of clay model studies. *BMC Zoology*,  
614 3(1), 6. <https://doi.org/10.1186/s40850-018-0033-6>

615 Schillé, L., Plat, N., Barbaro, L., Jactel, H., Raspail, F., Rivoal, J.-B., Castagneyrol, B., &  
616 Mrazova, A. (2025). Camera traps unable to determine whether plasticine models of  
617 caterpillars reliably measure bird predation. *PLOS ONE*, 20(3), e0308431.  
618 <https://doi.org/10.1371/journal.pone.0308431>

619 Schillé, L., Poirier, V., Raspail, F., Chaumeil, P., Bordenave, P., Herrault, P.-A., & Paquette, A.  
620 (2026). *Urbanization drives dietary specialization in insectivorous bird communities:*  
621 *Insights from a multi-prey cafeteria experiment monitored by innovative cameras.*  
622 <https://doi.org/10.64898/2026.02.25.707889>

623 Seimandi-Corda, G., Hood, T., & Cook, S. M. (2025). Understanding insect predator–prey  
624 interactions using camera trapping: A review of current research and perspectives.  
625 *Agricultural and Forest Entomology*, afe.12646. <https://doi.org/10.1111/afe.12646>

626 Seimandi-Corda, G., Hood, T., Hampson, M., Jenkins, T., Blumgart, D., Hall, J., Jowett, K.,  
627 Høye, T. T., & Cook, S. M. (2024). Identifying insect predators using camera traps reveal  
628 unexpected predator communities in oilseed rape fields. *Biological Control*, 198, 105636.  
629 <https://doi.org/10.1016/j.biocontrol.2024.105636>

630 Shaw, A., Pierson, T. W., & Holt, B. H. (2023). Clay Models and eDNA are Useful Tools for  
631 Identifying Predators of Salamanders. *Southeastern Naturalist*, 22(4).  
632 <https://doi.org/10.1656/058.022.0407>

633 Sittinger, M., Uhler, J., Pink, M., & Herz, A. (2024). Insect detect: An open-source DIY camera  
634 trap for automated insect monitoring. *PLOS ONE*, 19(4), e0295474.  
635 <https://doi.org/10.1371/journal.pone.0295474>

636 Smith, J. A., Suraci, J. P., Hunter, J. S., Gaynor, K. M., Keller, C. B., Palmer, M. S., Atkins, J. L.,  
637 Castañeda, I., Cherry, M. J., Garvey, P. M., Huebner, S. E., Morin, D. J., Teckentrup, L.,  
638 Weterings, M. J. A., & Beaudrot, L. (2020). Zooming in on mechanistic predator–prey  
639 ecology: Integrating camera traps with experimental methods to reveal the drivers of  
640 ecological interactions. *Journal of Animal Ecology*, 89(9), 1997–2012.  
641 <https://doi.org/10.1111/1365-2656.13264>

642 Stidsholt, L., Tena, E., Foskolos, I., Noguerras, J., De La Hera, I., Sánchez-Navarro, S., García-  
643 Mudarra, J. L., & Ibáñez, C. (2025). Greater noctule bats prey on and consume

644 passerines in flight. *Science*, 390(6769), 178–181.  
645 <https://doi.org/10.1126/science.adr2475>

646 Symondson, W. O. C. (2002). Molecular identification of prey in predator diets. *Molecular*  
647 *Ecology*, 11(4), 627–641. <https://doi.org/10.1046/j.1365-294X.2002.01471.x>

648 Thébault, E., & Loreau, M. (2005). Trophic Interactions and the Relationship between Species  
649 Diversity and Ecosystem Stability. *The American Naturalist*, 166(4), E95–E114.  
650 <https://doi.org/10.1086/444403>

651 Valdés-Correcher, E., Mäntylä, E., Barbaro, L., Damestoy, T., Sam, K., & Castagneyrol, B.  
652 (2022). Following the track: Accuracy and reproducibility of predation assessment on  
653 artificial caterpillars. *Entomologia Experimentalis et Applicata*, 170(10), 914–921.  
654 <https://doi.org/10.1111/eea.13210>

655 Vélez, J., McShea, W., Shamon, H., Castiblanco-Camacho, P. J., Tabak, M. A., Chalmers, C.,  
656 Fergus, P., & Fieberg, J. (2023). An evaluation of platforms for processing camera-trap  
657 data using artificial intelligence. *Methods in Ecology and Evolution*, 14(2), 459–477.  
658 <https://doi.org/10.1111/2041-210X.14044>

659 Windsor, F. M. (2023). Expanding network ecology in freshwater ecosystems. *Journal of Animal*  
660 *Ecology*, 1365-2656.13947. <https://doi.org/10.1111/1365-2656.13947>

661 Young, A., Stillman, R., Smith, M. J., & Korstjens, A. H. (2015). Scavenger Species-typical  
662 Alteration to Bone: Using Bite Mark Dimensions to Identify Scavengers. *Journal of*  
663 *Forensic Sciences*, 60(6), 1426–1435. <https://doi.org/10.1111/1556-4029.12839>

664 Zhao, B., & Andermann, T. (2026). Properties and Limitations of eDNA Substrates for Terrestrial  
665 Animal Monitoring. *Molecular Ecology Resources*, 26(2), e70096.  
666 <https://doi.org/10.1111/1755-0998.70096>

667 Zinger, L., Bonin, A., Alsos, I. G., Bálint, M., Bik, H., Boyer, F., Chariton, A. A., Creer, S.,  
668 Coissac, E., Deagle, B. E., De Barba, M., Dickie, I. A., Dumbrell, A. J., Ficetola, G. F.,  
669 Fierer, N., Fumagalli, L., Gilbert, M. T. P., Jarman, S., Jumpponen, A., ... Taberlet, P.

670 (2019). DNA metabarcoding—Need for robust experimental designs to draw sound  
671 ecological conclusions. *Molecular Ecology*, 28(8), 1857–1862.  
672 <https://doi.org/10.1111/mec.15060>

673 Zipkin, E. F., Zylstra, E. R., Wright, A. D., Saunders, S. P., Finley, A. O., Dietze, M. C., Itter, M.  
674 S., & Tingley, M. W. (2021). Addressing data integration challenges to link ecological  
675 processes across scales. *Frontiers in Ecology and the Environment*, 19(1), 30–38.  
676 <https://doi.org/10.1002/fee.2290>

677 Zvereva, E. L., Adroit, B., Andersson, T., Barnett, C. R. A., Branco, S., Castagneyrol, B.,  
678 Chiarenza, G. M., Dáttilo, W., del-Val, E., Filip, J., Griffith, J., Hargreaves, A. L.,  
679 Hernández-Agüero, J. A., Silva, I. L. H., Hong, Y., Kietzka, G., Klimeš, P., Koistinen, M.,  
680 Kruglova, O. Y., ... Kozlov, M. V. (2024). Predation on Live and artificial insect prey  
681 shows different global latitudinal patterns. *Global Ecology and Biogeography*, 33(11),  
682 e13899. <https://doi.org/10.1111/geb.13899>

683 Zvereva, E. L., & Kozlov, M. V. (2023). Predation risk estimated on live and artificial insect prey  
684 follows different patterns. *Ecology*, 104(3), e3943. <https://doi.org/10.1002/ecy.3943>