

Integrating multiple evidence streams to understand insect biodiversity change

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Title: Integrating multiple evidence streams to understand insect biodiversity change

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31 **Abstract**

32 Insects dominate animal species diversity yet face many threats from anthropogenic drivers of
33 change. Many features of insect ecology make them a challenging group, and the fragmented state
34 of knowledge compromises our ability to make general statements about their status. Here, we
35 discuss the challenges of assessing insect biodiversity change. We describe how multiple lines of
36 evidence – time series, spatial comparisons, experiments, and expert opinion – can be integrated to
37 provide a synthesis overview of how insect biodiversity responds to drivers. Applying this approach
38 will generate testable predictions of insect biodiversity across space, time, and changing drivers.
39 Given the urgency of accelerating human impacts across the environment, this approach could yield
40 a much-needed rapid assessment of insect biodiversity change.

41 Introduction

42 Insects are an extraordinarily diverse and abundant group of animals (1, 2), and are essential to
43 terrestrial and freshwater ecosystem functioning (3, 4) that is critical to human wellbeing (5). Most
44 of the world's flowering plant species depend on animal pollinators to reproduce, with an estimated
45 82% of species pollinated exclusively by insects (6, 7). Moreover, insects are a crucial trophic node
46 linking primary production to higher trophic levels: insects comprise the bulk of food sources for
47 many birds, bats, reptiles, freshwater fishes, and other vertebrates (8).

48 There is overwhelming evidence of changes in insect communities in recent decades. These changes
49 include rapid local and regional declines in abundance, occupancy, biomass, and diversity, as well as
50 the reorganization of communities (9–17). Concern over these changes has permeated across
51 scientific, public and policy sectors (11, 15–18). While some narratives have likely exaggerated the
52 extent of insect declines (22, 23), insects are clearly threatened by a combination of widespread
53 anthropogenic drivers, including land-use change, climate change, agricultural intensification,
54 pollution, and introduced species (14, 24).

55 Despite the growing recognition of the ecological and economic importance of insects (14, 25–28)
56 research on insect biodiversity has been limited (29, 30) and under-funded (31). As a result, the
57 available evidence describing insect trends is spatially, temporally, and taxonomically
58 unrepresentative (32, 33), such that the overall magnitude of the problem remains unclear (11, 23).
59 Current evidence is biased towards human-dominated landscapes in Europe and North America (13,
60 34, 35). Taxonomic bias favors easily observed or identified groups, such as butterflies, bees, and
61 dragonflies, while more taxonomically intractable or geographically isolated groups (e.g., parasitoid
62 wasps, earwigs, or icebugs) have been neglected (33). Available time series are generally short,
63 leading to extreme and potentially spurious inferences (36). The high interannual volatility of insect
64 populations means that long-term trends and historical drivers of insect biodiversity change are
65 particularly poorly captured by short time series (37). New approaches are required to understand
66 and quantify changes in insect biodiversity and its drivers, to better support global policy
67 recommendations and to target resources effectively to mitigate threats to insects. However, these
68 challenges are exacerbated by the fact that insects are hyper-diverse, have complex lifecycles, and
69 experience substantial population fluctuations.

70 For these reasons, a detailed global perspective of insect biodiversity change and its drivers remains
71 elusive (21), making it challenging to develop specific measurable targets and goals for insects in
72 large-scale biodiversity discussions and strategies (38). For example, Goal A of the Kunming-
73 Montreal Global Biodiversity Framework refers to metrics such as population abundance and
74 extinction risk, for which there are excellent data for vertebrates (39). In contrast, a mere ~1.2% of
75 insect species (12,100 species out of ~1 million described insect species (1)) have undergone the
76 International Union for Conservation of Nature (IUCN) Red List assessments necessary to calculate
77 extinction risk, of which approximately a quarter (3,107 species) were evaluated as Data Deficient
78 (40). An even smaller fraction has been assessed more than once, undermining any ability to
79 understand changes in extinction risk (40).

80 These shortfalls underline the need for new approaches to deliver a more comprehensive, globally
81 representative picture of the state of insects to inform scientific research, public understanding, and
82 biodiversity policies. Sparked by reports of unexpectedly large insect declines (9), there has been a
83 surge in the compilation and analysis of insect time-series data. While this effort has led to valuable
84 insights, disagreement remains as to whether, where and why insects are declining. The 'why'
85 question is particularly important because any attempts to reverse declines will need to address the

86 drivers of change. Moreover, a synoptic overview of insect biodiversity change and its drivers is a
87 prerequisite for making testable predictions about the effects of conservation or policy actions. For
88 example, how much would insects benefit if we reduced global pesticide usage. Indeed, prediction is
89 essential for demonstrating scientific understanding (41). A predictive understanding of insect
90 biodiversity change would make it possible to project the potential future state of insect biodiversity
91 and the consequences for ecosystems (e.g., the risk of reduced pollination services) and, thus,
92 inform evidence-based policy recommendations and conservation action.

93 Here, we address the grand challenge of understanding insect biodiversity change from fragmentary
94 data. Recent reviews on insect biodiversity have focused on the state of insects (2, 42), the drivers of
95 insect declines (13, 14), and advocated priorities for data generation (18, 37, 43). In this paper we lay
96 out the principles by which a more comprehensive understanding is possible via the integration of
97 multiple imperfect lines of evidence that are already available.

98 We first outline the features of insect biology that make them challenging to study. We then explore
99 the strengths and weaknesses of different evidence types for understanding how and why insect
100 biodiversity is changing. Finally, we identify what is required to harness the breadth of currently
101 available evidence to build a better understanding of the state of insect biodiversity. Our approach
102 provides a basis for advances in understanding the drivers of insect biodiversity change that are not
103 constrained by the limitations of only one evidence type. Our overall goal is to lay a roadmap toward
104 a solid understanding of insect biodiversity change on which conservation policies can be built,
105 without having to wait decades for comprehensive monitoring data.

106 The challenge of understanding insect biodiversity change

107 Insects are hyper-diverse, comprising up to 90% of all multicellular animal species, with the majority
108 still undescribed (1, 2). Beyond the numbers lie a staggering diversity of ecological adaptations and
109 functional roles, from eusocial pollinators, to specialized parasitoids, to scavenging detritivores (3, 4,
110 44), in addition to highly complex lifecycles (45). Thus, we should expect insect biodiversity change
111 to be extremely heterogeneous. Moreover, insect population sizes are more stochastic than for
112 other taxonomic groups, so more datapoints are required to capture fluctuations than for
113 vertebrates (46, 47). Stochasticity is high both within and between years, with even small differences
114 in the timing of annual monitoring resulting in dramatic differences in reported species abundance
115 (20, 21).

116 The complexity of insect biodiversity change is further compounded by a system of interacting
117 drivers (48, 49). At the local to landscape scale, there is strong evidence for land use, climate change,
118 pesticides, disease, and invasive species as key drivers of insect biodiversity change (2, 14, 50, 51).
119 What is lacking is a quantitative assessment of the relative importance of the various drivers across
120 scales, as well as knowledge on how these drivers interact to cause change. It is only by
121 understanding these complex and dynamic driver-response relationships that it will be possible to
122 identify when and where declines in insect biodiversity may be reversible (52) and deliver a synoptic
123 view of insect biodiversity change and its consequences.

124 Ecology and Traits

125 The impact of direct drivers of change is mediated by insect ecology and evolution. Species traits
126 have long been used to provide mechanistic insights into how biodiversity responds to drivers (53).
127 Traits are likely to be especially valuable for understanding differential responses to drivers in
128 insects, given the diversity of insect life histories and dearth of high-quality data. Indeed, as many
129 insects undergo metamorphosis, their ecological niche changes dramatically during their lifecycle,

130 such that environmental constraints on one life stage can be quite different to those on another
131 (54). Thus, insect life histories are highly variable, encompassing inherent differences in life stages
132 (e.g., larva vs adult), as well as in longevity, dormancy, synchronization (55), and reproductive
133 strategies (sexual vs asexual; egg laying vs viviparity). Moreover, understanding how species with
134 shared traits respond to drivers provides insights about the whole trait group, even when specific
135 data are not available for all (which is often the case for insects). For example, whether forest-
136 dwelling insects prefer open glades, closed understory, or forest canopy will influence how they
137 respond to deforestation (56, 57), and species preferences combined with rates of deforestation
138 could be used to infer insect trends.

139 Species' ecology can also interact with characteristics of the surrounding landscape to increase
140 susceptibility to decline (Fig. 1), with poorly dispersing or wingless species (58, 59) or those unable to
141 persist in certain habitat matrices (e.g. intensive agriculture) unable to survive (60). Better evidence
142 on how insect traits and life stages mediate the impact of drivers is crucial to understanding their
143 ongoing and future responses to global change (61).

144 Evolution and Plasticity

145 Global drivers subject insects to changing, and often strong, selection pressures, leading to
146 evolutionary responses that also mediate the effects of drivers on insect diversity (62). Thus,
147 understanding and predicting insect responses to environmental change is complicated by
148 evolutionary dynamics and vice versa (63, 64). For instance, dispersal, driven by land-use change,
149 can shape the spatial pattern of insect genetics (65). Similarly, crop domestication has selected for
150 some insects to become agricultural 'pests' (66, 67).

151 Insects exhibit various examples of beneficial adaptive plasticity in response to environmental
152 change, including diapause induction or suppression of reproductive output under harsh conditions
153 (68). However, insects may also pursue maladaptive pathways (i.e., developmental traps). For
154 example, climate change in the temperate zone is causing insects to complete their lifecycles more
155 quickly, leading some to attempt additional generations (and often fail) before winter sets in (69).
156 These short-term changes in turn impact insect population dynamics and can be translated into long-
157 term adaptation. Temperature changes are a key driver of evolutionary adaptation in insects, and as
158 suitable climates shift, insects are challenged with adapting to new conditions or tracking suitable
159 ones (72). Conversely, pesticide resistance may actively select for certain species in agricultural
160 settings, increasing their abundance while the majority are adversely affected (73). We must
161 therefore consider adaptive capacity and plasticity in response to environmental drivers, since
162 evolutionary rescue effects will be more apparent for insects than for longer-lived organisms (76,
163 77).

164 Interaction networks

165 Insect populations are influenced by a range of antagonistic (e.g., predation or herbivory) and
166 facilitative (e.g., pollination) interactions (Fig. 1). The consequences of environmental change for
167 insects depend both on how they interact with other species and the structure of the whole
168 network. Insect species often have specialized interactions, including as parasitoids, herbivores, or
169 pollinators (78, 79). For example, 27% of tropical herbivorous insects feed exclusively on a single
170 host plant species, while 48% feed on plants within one genus and 60% within one family (80).
171 Holometabolous insects (those with complete metamorphosis) experience shifting interactions
172 throughout their lifecycles (e.g., many hoverflies change from predatory larvae to facultative
173 pollinators as adults). This makes insects especially vulnerable to co-extinctions with their
174 interaction partners (81, 82). Furthermore, the loss of generalist insect species may have wide

175 ranging consequences on network resilience and robustness through cascading extinctions (63),
176 potentially resulting in coextinction of species with no direct interaction (84). These complexities
177 mean that drivers that may superficially appear unimportant for certain species may still have
178 consequences through indirect effects (82).

<FIGURE 1 HERE>

179 **Emerging questions**

180 These layers of complexity highlight the magnitude of the challenge in modeling insect biodiversity
181 change from fragmentary data, but also suggest some emerging questions: which drivers are most
182 important, for which insects, and what is the form and timing of the response? Can we extract
183 sufficient signal to understand – broadly, if not precisely – the drivers of global change in insects, in
184 models that are good enough to be useful for informing policy change or mitigation measures?
185 Given the urgent need to address insect declines (85), we need to make better use of the data that is
186 currently available.

187 **Time series are not enough**

188 Time series are comparable estimates of a biodiversity metric (e.g., population abundance, biomass)
189 at a location at multiple points in time. Time series are therefore a direct form of evidence for
190 biodiversity change, capturing the actual temporal dynamics of interest, and evidence from time
191 series has formed a major part of current knowledge on insect change (11, 86). Individual time series
192 vary in their temporal, spatial, and taxonomic coverage, while time series are undertaken for diverse
193 reasons, including monitoring associated with recovery following restoration, post pollution or
194 weather events, or in habitats known to be under threat. Collectively, the portfolio of existing insect
195 time series is neither spatially nor taxonomically representative (35). These issues hinder our ability
196 to use time series to quantify how insect biodiversity is changing at global and regional scales, and
197 limit how well we can identify the causes of change (43).

198 The temporal coverage of individual time series varies in terms of the *frequency* (number of
199 sampling occasions) and the *span* (the length of time between the first and last samples) of the
200 period assessed (Fig. 2). Ideally, the frequency of data collection would be sufficient to capture
201 change from one generation to another, whilst accounting for within-season variation (e.g., as adults
202 emerge and then die). Instead, most insect time series contain gaps (35, 37), and many represent
203 ‘snapshot’ resurveys of locations sampled once in the past (13% of studies analyzed in van Klink et al.
204 (11); Fig. 2). Snapshot surveys are particularly problematic for insects, where year-to-year population
205 variation can be much higher than for plants or vertebrates (20), creating substantial noise in the
206 trend estimate and extreme sensitivity to the baseline conditions (21, 55). This noise can introduce
207 bias if there is any non-randomness in the circumstances of either the original or repeat survey (87).
208 As a result, intermittently sampled (i.e., less frequent than annual sampling) time series spanning
209 fewer than ten years are unlikely to provide reliable estimates of change in insect populations (21,
210 46, 87). But with little support for long-term monitoring (20), data are more typically collected over
211 much shorter periods. Even for longer time series, the frequency and span of available time series
212 (Fig. 2) means they often lack the statistical power to detect trends (21, 36, 52, 88) or isolate
213 associated drivers (43).

<FIGURE 2 HERE>

214 An essential quality for time-series data is that the sampling protocol should be consistent over time,
215 so that comparable estimates of biodiversity are obtained (or that variation, e.g., due to surveyor
216 identity, can be statistically accounted for). However, consistency is not sufficient for producing data
217 that can inform the wider question of why insect biodiversity is changing. Collections of time-series
218 data will only provide such information if they are representative of environmental gradients and
219 the range of exposure to threats (90). Instead, site selection is often non-random, with many time
220 series located at field stations or other areas likely to be buffered from ongoing threats (35, 87) (e.g.,
221 34% of plots in the meta-analysis by van Klink et al. (11) are located in protected areas). By contrast,
222 other time series may have been initiated in response to an environmental perturbation, either
223 natural (such as a weather event), catastrophic (e.g., pollution) or artificial (e.g., experimental,
224 restoration or changing management). In the absence of matching controls, these data have the
225 potential to skew our perception of how and why insect biodiversity is changing (32). Resource
226 limitation typical to long-term sampling strategies may also mean that sampling effort is limited,
227 raising questions as to the power to identify trends in some populations.

228 A further issue is that most time series lack scale-relevant information on external drivers and how
229 they changed over time. Where this information is available, these drivers are often correlated and
230 difficult to disentangle, which limits the ability of time-series data to attribute the causes of
231 biodiversity change (10, 91, 92). Without quantification of how drivers affect insect diversity (e.g.,
232 driver decomposition; (93, 94)) we cannot hope to predict how alternative policies and actions will
233 affect future trends.

234 Sparked by the debate on insect biodiversity change, there have been calls to address the issues
235 outlined above by greatly expanding the network of insect monitoring schemes (18, 37, 52). For
236 instance, Didham et al. (21) suggested that intensive annual monitoring (e.g., (95)) could be
237 complemented by extensive but infrequent occupancy surveys at large numbers of sites. A step-
238 change in insect monitoring is indeed urgently required, and well-designed, long time series will
239 ultimately provide the best quantification of biodiversity change (although attribution to drivers will
240 remain difficult). However, the cost of ongoing inaction will be high, and we cannot wait decades to
241 accumulate these data (17, 34, 86); there is enough evidence about insect declines in some regions
242 to demand immediate remedial action (85). To target action where it is most needed, we require a
243 rapid synthesis on the causes of insect biodiversity change using data from a broad range of
244 evidence types, not from just time series.

245 Evidence beyond time series: developing threat-response models

246 Time series provide the best evidence that change has happened but struggle to tell us why that
247 change occurred. Understanding why biodiversity has changed is critical if we are to reverse
248 declines, prevent extinctions, and maintain ecosystem function into the future (41, 96). To build a
249 predictive understanding of insect biodiversity change we need to first model the relationships
250 between biodiversity metrics and direct drivers. We refer to these relationships as threat-response
251 models (TRMs; sensu (97), also known as pressure-impact relationships (98)). By quantifying the
252 relationships between drivers and biodiversity metrics, it becomes possible to project the
253 biodiversity response across spatial domains where the driver intensity is known. In this way, TRMs
254 can be used to summarize the total impact of a driver within a given domain, and to make testable
255 predictions for regions where no biodiversity data exists. Projecting TRMs in time makes it possible
256 to re-evaluate historical baseline conditions (99) and compare biodiversity trends under a range of
257 plausible futures of climate and socioeconomic change (96).

258 Well-established TRMs, such as those developed as part of the GLOBIO (98) and PREDICTS (100)
259 projects, are parameterized largely using data from vertebrates. However, the ability of TRMs to
260 simplify multidimensional responses using trait-based approaches makes them particularly valuable
261 for insects (and other hyper-diverse groups). The notion of using models to link insect biodiversity
262 with threat gradients has been gaining traction in recent years, with insights from studies at local
263 (101), regional (102) and global (48) scales. More broadly, insect conservation biologists have argued
264 that experimentation (43) or spatial comparisons (52) can be employed to build models and reveal
265 the most important drivers of insect biodiversity change. Where rigorous data is lacking, models
266 linking insect populations with threats can also be derived from eliciting the opinion of taxon
267 experts, using techniques from the social sciences (51, 103). Such approaches are particularly
268 valuable for understudied taxa or geographic regions where structured expert opinion processes can
269 provide key insights about population declines in the absence of quantitative data. These and other
270 types of approaches all provide useful evidence, in the form of TRMs, to augment what can be
271 learned from population time series.

272 The ideal dataset for building TRMs would measure change over a long period, have broad
273 taxonomic and spatial coverage, and represent the full range of drivers. In reality, few biodiversity
274 datasets come close to this ideal, although for well-studied groups such as birds and mammals they
275 are sufficient for building useful TRMs. The evidence streams available for insects occupy different
276 spaces along these three axes (Fig. 3): in other words, the available evidence types have
277 complementary strengths and weaknesses.

278 <FIGURE 3 HERE>

279
280 To illustrate these complementarities, we evaluate each evidence type against six ‘ideal properties’
281 (Fig. 4) for understanding and predicting insect biodiversity change. These are 1) the ability to
282 describe long-term trends, 2) the ability to capture transient dynamics, 3) whether the results of
283 analyzes using the evidence type can be decomposed or aggregated across taxonomic and spatial
284 scales, 4) whether the results of analyzes using the evidence type can be generalized and
285 transferred, 5) whether corresponding driver information is available at the same scale as the
286 evidence type, and 6) whether the evidence type can unpick mechanistic or causal threat-response
287 relationships, including interacting (e.g., antagonistic, synergistic, additive) drivers.

<FIGURE 4 HERE>

288 Experiments

289 The strength of experiments lies in their ability to confirm causal links between drivers and
290 biodiversity metrics (43). Experiments vary along a spectrum from lab-based, to plot or semi-field
291 studies, up to more challenging landscape-scale manipulations (104). Whilst experiments deliver
292 strong evidence, it is difficult to translate the outcomes to real world spatial and temporal scales
293 (91). For instance, lab-based experiments are often targeted at individual species (minimal
294 taxonomic breadth; Fig. 3) to characterize their response to a single factor e.g., thermal optima or
295 agrochemical exposure (49, 105), and are often short-term (106) (low temporal breadth; Fig. 3).
296 Whilst experiments provide an opportunity to identify causal relationships, the scope of
297 environmental drivers manipulated is typically limited (i.e., low environmental breadth; Fig 3) and so
298 may only partially capture causes of declines. Moreover, experiments often fail to capture how

299 responses to drivers change when species are embedded in real interaction networks (Fig. 1)
300 (although natural experiments are increasingly common (107)). Thus, simply scaling up the results of
301 small-scale experiments may not be informative (108).

302 Ultimately, while experiments are common, there are few at a large enough spatial and temporal
303 scale to fully capture real-world effects (91), reflecting practical and financial constraints (109).
304 These limitations can be partially mitigated in distributed collaborative experiments (99) or
305 transcended by synthesizing results across multiple experiments using meta-analysis. Combining
306 multiple experiments provides a means to quantify generalized relationships between
307 anthropogenic threats and insect diversity (90). Still, meta-analyses are subject to their own
308 limitations, such as publication bias (110), inferential errors (111) and lack of data availability (112,
309 113). Nevertheless, meta-analytic approaches have already been effective in assessing the average
310 response of insects to drivers including urbanization (114), dams (115), and nutrient enrichment
311 (116, 117).

312 Spatial comparisons

313 Spatial comparisons – the comparison of biodiversity across sites – are often used to investigate
314 insect biodiversity change (48, 118, 119). Their use assumes that patterns in space can shed light on
315 patterns over time (120, 121). For example, Hallmann *et al.* (9) synthesized data from 63 sites within
316 protected areas in Germany – most visited only once – to infer a 27-year time series of flying insect
317 biomass.

318 Spatial comparisons have high statistical power to identify relationships between drivers and
319 biodiversity declines and quantify their potential impact (52). Indeed, comparisons across whole
320 landscapes allow sites to be compared across multiple driver gradients, e.g. (118). In addition, larger-
321 scale changes can be modeled by bringing such comparisons together. For example, the PREDICTS
322 project has compiled a global database of hundreds of studies comparing sites differing in land use
323 types and intensity (122). TRMs built with these data have estimated average responses of
324 biodiversity metrics across land-use gradients, including for insects (48, 123), and projected these
325 responses in space and time (100).

326 Spatial comparisons have limitations for assessing changes in insect biodiversity (91, 124). They are
327 correlative, limiting causal inference, since correlation between drivers makes their effects hard to
328 separate (although see (125)). By taking snapshots in time they risk being confounded by transient
329 dynamics and legacies of site history, and they overlook gains or losses in the regional species pool
330 (an aspect of ‘shifting baseline syndrome’ (126)). The advantage, however, lies in the relative
331 simplicity of assembling the evidence base: they often sample more sites, can be undertaken in
332 more locations (91) and, given the statistical power with which they link spatial variation in
333 biodiversity and drivers, have so far been undervalued as evidence of insect biodiversity change (52).
334 Perhaps most importantly, their collection can be achieved in very short time scales and can be
335 reactive in terms of their focus, including under-represented regions, habitats, or taxonomic groups.

336 Expert elicitation

337 Information from experts (including scientists, indigenous people, and other non-scientist
338 specialists) reflects their accumulated knowledge and experience. Expert elicitation around
339 biodiversity trends, and the drivers thereof, is particularly valuable for poorly studied insect groups,
340 in the absence of more direct forms of evidence. Expert elicitation may also provide insights into the
341 impact of multiple interacting drivers on better-studied groups, which may be difficult to disentangle
342 quantitatively but can be teased apart conceptually (127, 128). A major limitation is the subjective
343 nature of expert knowledge, which makes assessing the reliability and repeatability of results

344 challenging, especially when very few experts are available (14, 30). Similarly, the process of expert
345 elicitation may introduce its own bias through survey design and choice of questions as well as
346 interactions between participants in group meetings, although approaches such as the Delphi
347 technique can be used to reduce some of these issues (129).

348 Given sufficient expertise, expert elicitation has the potential for high taxonomic and geographic
349 coverage. It provides information that may be costly to gather in other ways (e.g. large-scale, long-
350 term monitoring), although detailed species assessments (e.g., IUCN Red List assessments) can be
351 time, data and cost intensive. At a broader scale, Miličić *et al.* (51) used a top-down expert elicitation
352 process to gather information from 413 respondents on the most relevant threats to insect
353 biodiversity in general, highlighting key differences between regions and taxa. This indirect evidence
354 can be used to link the state of insect biodiversity with specific threats, especially where direct
355 evidence is not available, or as a comparison to other types of evidence.

356 Harnessing the breadth of evidence

357 We have explored how TRMs based on experiments, spatial comparisons and expert elicitation
358 provide alternative and complementary sources of evidence linking insect biodiversity change with
359 drivers. Crucially, none of these evidence types alone can cover the full taxonomic, spatial, or
360 temporal dimensions required for a synoptic and predictive understanding of insect biodiversity
361 change (Figs. 3 and 4). Thus, there is an urgent need to harness this breadth of evidence, to
362 synthesize the inferences from each evidence type in ways that maximize the complementarities and
363 overcome the limitations of individual evidence types. To do this, we need to understand how to
364 integrate diverse evidence streams and explore the limits to which we can combine TRMs and
365 extend their inferences to different taxonomic, spatial, or temporal settings. Without attempts to
366 generalize, the literature could become a descriptive ‘stamp collection’ of case studies (90).

367 One avenue for combining evidence is through model-based data integration, in which the
368 relationship between data types is defined in terms of model parameters (130, 131). Integrated
369 modeling is particularly well developed in the context of species distribution models. For instance,
370 Kotta *et al.* (132) combined experimentally defined tolerance levels with spatial data to model
371 climate change effects on a macroalgal species and its herbivore. Domisch *et al.* (133) combined
372 freshwater species occurrence information with expert range data leading to improved spatial
373 predictions. Whilst integrated modeling is conceptually attractive, there are analytical challenges,
374 particularly when combining data that differ in both quality and quantity (134) and where there are
375 mismatches in spatial scale among data types (135). As a result, formal data integration may
376 currently only be possible for well-studied regions and taxa where data availability is highest. This
377 starting point, however, is fertile ground for new modelling tools to be developed (136).

378 A tractable alternative is to compare the predictions from different types of TRM against one
379 another, by projecting the models across space (e.g., using spatial data layers) and taxa (e.g., using
380 species traits). Regions of parameter space where the model projections agree about the direction
381 and/or magnitude of biodiversity change indicate higher confidence in the state of insect
382 biodiversity. Regions where they disagree highlight priority research gaps or model inadequacies.
383 Regions where direct evidence of biodiversity change is available (i.e., time series) provide an
384 opportunity for external validation (90, 137) and a chance to demonstrate predictive understanding
385 (41). This opens up a range of options for iterative model refinement to achieve the best fit to
386 empirical data (known as a ‘digital twin’ (138)). For example, one could apply weights to each
387 evidence type (139), then solve for the weights that optimize fit to the observed time-series trends,
388 or test for lagged responses to increases in threat intensity (140). Similarly, when integrating TRMs

389 for different threat types, one could compare models that assume additivity among threats with
390 those in which the threats act synergistically or antagonistically.

391 Synthetic TRMs integrating evidence types and drivers would provide a starting point to answer
392 some of the biggest questions about insect biodiversity change (Fig. 5). Projecting the model in space
393 would make it possible to assess the magnitude of insect biodiversity change across large scales and
394 to identify probable hotspots of decline. Projecting the model in time would make it possible to
395 explore plausible future scenarios for insect biodiversity (96). Aggregating insects by functional traits
396 (e.g., body size, diet, fecundity, etc.) (141) that underpin ecosystem processes would make it
397 possible to explore the consequences of insect biodiversity change for higher trophic levels
398 (especially insectivorous bats and birds) and on benefits that people derive from insects (including
399 pollination, pest control and nutrient cycling, amongst others (3, 4)). The modeling framework
400 described here is also easily extensible to incorporate indirect drivers and the effects of mitigation
401 strategies such as protected areas (96, 142). Based on these principles, a broad-brush quasi-global
402 model of insect responses to land-use is within reach (*sensu* (48, 100)), as are regional models of
403 multiple threats for well-studied Orders.

<FIGURE 5 HERE>

404 Whilst powerful, models have limitations. We see four major challenges for the development of
405 large-scale and credible TRMs for insects. The first is around the technical aspects of model-fitting.
406 There are well-known difficulties of modeling biodiversity using heterogenous data (144), especially
407 where the scale of inference is different from the scale of the data (135) or where there is context-
408 dependency (111). A second challenge is around scale: TRMs built to address global questions (e.g.
409 about the net magnitude of change) will not be suitable for addressing local questions (e.g. about
410 the effect of a given intervention). Thus, TRMs at different scales will be appropriate for addressing
411 different questions, but identifying the appropriate level of detail for a particular application may
412 not always be obvious. The third challenge is around communication: it will be important for models
413 to capture and convey the many forms of uncertainty and validity (90, 145). However, inferences
414 around biodiversity change are often confounded by temporal, spatial and phylogenetic clustering
415 within the data. Capturing all these uncertainties risks rendering the model uninformative for
416 decision-making (145, 146). Similarly, it will be important to avoid making unwarranted claims about
417 generality (90), particularly when presenting models as being of global relevance (147). Formal
418 analysis of the degree to which models can be validly extended (i.e., transferability) is useful to place
419 limits on the potential inference and should become standard (148, 149). Finally, there are ecological
420 challenges that will be hard to overcome: certain aspects of insect ecology will be especially hard to
421 model (as noted in Section 2). Early generations of insect biodiversity projection models will be
422 unable to capture complex life histories or species interactions, but these and other processes could
423 be added later (143). There are taxonomic groups and parts of the world where almost nothing is
424 known about the insect fauna. Thus, one of the goals for the first generation of synthetic insect
425 TRMs would be to highlight the remaining gaps (gaps not covered by data or by valid model
426 inferences) where new data are urgently needed.

427 Outlook

428 Even with the caveats outlined above, there is sufficient evidence of changes in insect biodiversity to
429 demand urgent action (85). This action needs to be informed and directed by a strong evidence base
430 (i.e., sufficient extent, depth, and representativeness of evidence across time, space, and taxonomy,
431 with levels of uncertainty that allow for clear decisions). Intergovernmental commitments to avert

432 biodiversity loss will always be limited, so resources must be used effectively. Even when
433 commitments are made, the historic track record of meeting such goals has been less than
434 impressive (150). The recent Global Biodiversity Framework provides new impetus for action, with
435 an ambitious target for the reduction of pressures on natural systems by 2030, and a goal (amongst
436 others) to achieve healthy and resilient populations of wild species by 2050. There is an urgent need
437 for the biodiversity modeling community to evaluate whether the scale of ambition defined in the
438 targets is sufficient to put us on a pathway toward the 2050 goal, i.e. to 'bend the curve' (96). Due to
439 the sheer number of insects, their vast ecological diversity and the paucity of available data, the
440 challenge of understanding global insect biodiversity change is an immense task. To date, limited
441 resources have been directed toward this task. We are not the first to point out that time series of
442 insect populations alone are insufficient to address this problem (43, 52). We have gone further in
443 arguing that a broad suite of evidence types, brought into a common analytical framework, is
444 required to evaluate the scale of the problem facing insect biodiversity, as well as providing a triage
445 system to identify the highest priority taxa, places, and threats, and thus leverage points where
446 mitigation can be most effective. Only through harnessing the full breadth of available evidence can
447 we piece together the fragmentary data into a coherent picture. It is a small but important first step
448 toward an insect-positive future.

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902 Writing - Original Draft: RC, CLO, AJB, JM, JGR, ZD, EED, TN, AP, BAW, NJBI

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904 Visualization: RC, CLO, NJBI

905 Project administration: RC, CLO, NJBI

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908 **Competing interests:** Dr. Lynn Dicks is a Board Member of Natural England, the UK Government's
909 statutory advisor for the natural environment in England. Dr. Nick Isaac is a member of the
910 Biodiversity Expert Committee of the UK Government Department of Agriculture, Food and Rural
911 Affairs, and of the European Commission expert group on Pollinating Insects.
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913 **Data and materials availability:** All data used in the manuscript are previously published (89).

914 **Figure Legends**

915 **Fig. 1. The complexity of insects in a changing world and the role of interactions.** The center ring
916 shows an example insect lifecycle, with curved arrows between life stages (here, larva, pupa, adult).
917 Connected to the lifecycle are a simplified number of interacting species including a variety of
918 taxonomic groups. The middle ring represents the landscape in which this lifecycle and the local
919 interactions occur, often incorporating multiple habitat types and land uses. The outer ring shows
920 some of the major drivers that act across the landscape and local scales, affecting the species found
921 in those areas. These can act alone but can also interact.

922 **Fig. 2. Frequency vs span of time series in a large insect time series database.** The points represent
923 the 1,657 sites (i.e., time series) included in the InsectChange database (89), which underpins a
924 large-scale meta-analysis on insect trends (11). Note that only time series covering ~10 or more
925 years were included in this database. The color underneath the points reflects the density of time
926 series across the plot (red = highest density, white = lowest density). The lines represent
927 approximately annual sampling (i.e., 10 sample events for a 10-year time series), ~seasonal sampling
928 (i.e., 40 sample events for a 10-year time series), ~monthly sampling (i.e., 120 sample events for a
929 10-year time series), ~weekly sampling (i.e., 520 sample events for a 10-year time series).

930 **Fig. 3. The power of attribution and breadth of coverage of different evidence types for insect
931 biodiversity change across temporal, spatial/environmental, and taxonomic dimensions.** Power of
932 attribution refers to the potential for evidence types to identify causal links between insect
933 biodiversity change and any external driver based on existing data. Experiments have high power
934 because they are designed to quantify specific effects, whereas time series are typically set up
935 without regard to the drivers present. Coverage captures the extent, depth, and representativeness
936 of the evidence type in the three dimensions of time, space, and taxonomy. For example, taxonomic
937 coverage reflects the number of insect Orders included (extent), the number of species within
938 Orders (depth), and the representation of species across Orders (representativeness). Although
939 inherently subjective, positioning of the shapes illustrates our interpretation of the strengths and
940 weaknesses of the four evidence types; the size of each shape indicates the approximate variation in
941 power of attribution and coverage within each evidence type. N.B. Evidence types are not mutually
942 exclusive, e.g., some studies can be both experiments and time series, depending on how data were
943 collected and analyzed.

944 **Fig. 4. Properties of available data for understanding insect biodiversity change and underlying
945 drivers.** Grades and shading (A – greatest, dark to D – least, light) reflect the fulfilment of the ideal
946 property for each evidence type. Each box contains our rationale for the assignment of grades to
947 each property and evidence type.

948 **Fig. 5. Establishing a synoptic overview of insect biodiversity change to inform policy and
949 conservation action.** Integrating multiple evidence types on the state of and changes in insect
950 biodiversity with information on the drivers of this change can provide a synoptic overview of
951 current patterns. This overview would underpin projections of insect biodiversity change across
952 space and through time, as well as of the potential consequences of insect biodiversity change.