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## **ROBITT: a tool for assessing the risk-of-bias in studies of temporal trends in ecology**

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# 1 **ROBITT: a tool for assessing the risk-of-bias in studies of** 2 **temporal trends in ecology**

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20

## 21 **Abstract**

22 1. Aggregated species occurrence and abundance data from disparate sources are increasingly  
23 accessible to ecologists for the analysis of temporal trends in biodiversity. However, sampling biases  
24 relevant to any given research question are often poorly explored and infrequently reported; this has  
25 the potential to undermine statistical inference. In other disciplines, it is common for researchers to  
26 complete “risk-of-bias” assessments to expose and document the potential for biases to undermine  
27 conclusions. The huge growth in available data, and recent controversies surrounding their use to infer  
28 temporal trends, indicate that similar assessments are urgently needed in ecology.

29 2. We introduce ROBITT, a structured tool for assessing the “Risk-Of-Bias In studies of Temporal Trends  
30 in ecology”. ROBITT has a similar format to its counterparts in other disciplines: it comprises signalling  
31 questions designed to elicit information on the potential for bias in key study domains. In answering  
32 these, users will define study inferential goal(s) and relevant statistical target populations. This  
33 information is used to assess potential sampling biases across domains relevant to the research question  
34 (e.g. geography, taxonomy, environment), and how these vary through time. If assessments indicate  
35 biases, then users must clearly describe them and/or explain what mitigating action will be taken.

36 3. Everything that users need to complete a ROBITT assessment is provided: the tool, a guidance  
37 document, and a worked example. Following other disciplines, the tool and guidance document were  
38 developed through a consensus-forming process across experts working in relevant areas of ecology and  
39 evidence synthesis.

40 4. We propose that researchers should be strongly encouraged to include a ROBITT assessment when  
41 publishing studies of biodiversity trends, especially when using aggregated data. This will help  
42 researchers to structure their thinking, clearly acknowledge potential sampling issues, highlight where  
43 expert consultation is required, and provides an opportunity to describe data checks that might go  
44 unreported. ROBITT will also enable reviewers, editors, and readers to establish how well research  
45 conclusions are supported given a dataset combined with some analytical approach. It should also  
46 strengthen evidence-based policy and practice, reduce differing interpretations of data, and provide a  
47 clearer picture of the uncertainties associated with our understanding of ecological reality.

48 **Key words**

49 risk-of-bias; species occurrence data; temporal trends; Essential Biodiversity Variables; indicators;  
50 uncertainty; insect declines

51 **Introduction**

52 Species occupancy and abundance are fundamental state variables in ecology. Understanding the rates  
53 at which these variables are changing is required to monitor progress towards biodiversity targets and  
54 the effects of conservation interventions. Ultimately, this information comes from data documenting  
55 the detection of one or more individuals of some taxon; that is, species occurrence data, or, in some  
56 countries, “biological records” (note that here we also use these terms to cover abundance data, as such  
57 information may be considered an occurrence attribute). Species occurrence data from disparate  
58 sources are often combined and analysed statistically to derive measures of biodiversity over large  
59 taxonomic, spatial, and temporal extents (e.g. Gregory et al., 2005). Indeed, this is the premise of  
60 species population “Essential Biodiversity Variables” (Jetz et al., 2019; Kissling et al., 2018; Pereira et al.,  
61 2013). The temporal component of these data products may be averaged over spatial and taxonomic  
62 domains to produce indicators (GEO BON, 2015); these have become a key source of information on  
63 ecological change for policy makers (Navarro et al., 2017). Frequently then, evidence of temporal trends  
64 in biodiversity is derived through the statistical analysis of species occurrence data.

65 Species occurrence data vary widely in terms of why and how they were recorded, and the information  
66 that they provide. Presence-only data document the sighting of some species, with information on  
67 where and when the sighting occurred. These data are derived from a variety of sources, including  
68 natural history collections in museums and herbaria, surveys by professional biologists, and various  
69 types of data collected by volunteer naturalists (Collen et al., 2013). Presence-absence data provide  
70 additional information on sampling events which did not yield a detection of the focal taxon. These data  
71 are most likely to be collected through structured monitoring schemes using specific protocols (but see  
72 Sullivan et al., 2014). Abundance data can provide more information still: they document the number (or  
73 other quantity) of individuals. All of these data can be used to provide information on trends in  
74 biodiversity.

75 In recent years, species occurrence data have increased in volume and accessibility. This can be ascribed  
76 to several initiatives: the digitization of historic biological records (Page et al., 2015); the proliferation  
77 and growth of citizen science monitoring initiatives (Spear et al., 2017); the launch of online data  
78 aggregators such as GBIF and similar regional portals (Nelson and Ellis, 2019); and the compilation of  
79 more specialist databases focused on particular types of ecological community (Dengler et al.,

80 2011), monitoring data (Dornelas et al., 2018) or other evidence types (Hudson et al., 2017). Thanks to  
81 these initiatives, it is now straightforward for ecologists to access large quantities of data, and to use  
82 them for research. However, data quantity does not necessarily equal quality of scientific insight, and  
83 there have been important questions raised concerning the suitability of some biodiversity data for  
84 drawing reliable inferences about change over time (e.g. Ball-Damerow et al., 2019; Cardinale et al.,  
85 2018; Pescott et al., 2019).

86 To appreciate the potential challenges associated with the analysis of heterogeneous data, it is useful to  
87 define some key statistical concepts (see Box 1 in supplementary material 2 for a glossary of relevant  
88 terms). Whilst there are many possible definitions of statistics (Barnett, 1982), one typical conception is  
89 that of reasoning under uncertainty and inherent variability, with classical texts (e.g. Lehmann, 1959)  
90 focusing on the use of observed data to make inferences concerning unobserved distributions. For  
91 example, monitoring-type investigations can be appreciated as a sample-based approach to  
92 understanding features of some broader environment; likewise, smaller-scale experiments are normally  
93 conducted with generalisation in mind. In both these cases it is rarely feasible to census an entire  
94 population of interest: researchers use samples. This leads to questions concerning the validity of  
95 inferences. One assessment of a study's validity is to ask whether these inferences are well-supported  
96 by the data in hand (internal validity). For sample-based results to be generalisable, however, they must  
97 also be true of the wider population of interest (external validity). A study's external validity is likely to  
98 be undermined if samples are not representative of the population with respect to important features  
99 for the desired inferences (Meng, 2018); this is often known as "sampling bias", or sometimes "selection  
100 bias".

101 To obtain a representative sample, researchers would ideally select individual units randomly from the  
102 population (probability sampling). However, this is often impractical, in which case researchers might  
103 make use of nonprobability samples, such as those found in aggregated biodiversity databases; these  
104 are samples that were not necessarily collected to be representative of a clearly defined population.  
105 Small samples may also be unrepresentative of important features by chance, even if they are  
106 probability samples. Before researchers can understand a sample's representativeness, they must first  
107 define their research question and statistical target population.

108 In studies of biodiversity trends, researchers tend to define their statistical populations along the axes of  
109 space, time, and taxonomy (e.g. Dennis et al., 2019; Outhwaite et al., 2019; Powney et al., 2019; van  
110 Strien et al., 2019). For example, one might be interested in trends in bird distributions in North America  
111 over the period 1950 to the present day. It is also worth noting that, although they may not always be  
112 defined explicitly, other axes may be important for inference. For example, researchers may be more  
113 interested in whether samples represent all areas of some multi-dimensional environmental space (e.g.  
114 as defined by a set of climatic variables), rather than just being considered representative of geographic  
115 space. Likewise, for some purposes, representative coverage of species' traits may be desired along  
116 with, or instead of, even phylogenetic coverage. To be representative of such populations, data should  
117 be representative of all axes. To illustrate this point using the above example, data would need to be  
118 sampled as close to randomly as possible across North America, across all relevant bird species, and  
119 evenly between 1950 and the present day. Otherwise, it is possible that the data will be  
120 unrepresentative of the populations of interest. For example, particular geographical areas may be over-

121 or under-sampled at particular times, leading to a confounding of time and space, and, ultimately,  
122 conclusions that bear little resemblance to the true state of nature.

123 There are many situations in which occurrence data are unlikely to be representative of the statistical  
124 populations implied by studies of biodiversity trends. Data collected opportunistically are highly likely to  
125 be non-random along the key axes of space, time, and taxonomy (or other important dimensions).  
126 Volunteer naturalists, for example, tend to preferentially sample accessible and attractive locations, and  
127 interesting species (Barends et al., 2020; Prendergast et al., 1993). Structured data, collected according  
128 to some sampling design, may well be representative of some set of domains; however, when multiple  
129 datasets, with different aims, extents, and protocols, are aggregated (e.g. as on GBIF), then the target  
130 population to which these data pertain becomes unclear. To illustrate this point, imagine several  
131 datasets, each derived from structured monitoring of some taxon in some spatial unit at regular time  
132 intervals. These data might be very informative about change in those units (but see Gonzalez et al.,  
133 2016), but there is no reason to suppose that they can be combined and used to draw robust inferences  
134 about some wider geographic domain, unless the samples happen to resemble a probability sample of  
135 the broader population(s) of interest (Cardinale et al., 2018). The problem of a mismatch between  
136 sample and population could be reduced or avoided if researchers first assessed their data to inform  
137 readers of their choice of population and the scope of their inferences.

138 The frequent mismatch between sample and statistical target population in studies of biodiversity  
139 trends has not gone unnoticed; indeed, it is a common subject for critical comments on studies in the  
140 literature. For example, Sánchez-Bayo and Wyckhuys (2019) and van Klink et al. (2020) were criticised  
141 for extrapolating their claims of insect declines beyond the taxonomic and geographical limits of their  
142 data (Desquilbet et al., 2020; Jähnig et al., 2021; Saunders et al., 2020; Simmons et al., 2019). Vellend et  
143 al. (2013) and Dornelas et al. (2014) were criticised for concluding that local species richness is not in  
144 decline globally from meta-analyses of studies that were geographically biased in relation to human  
145 disturbance and species richness itself (Cardinale et al., 2018; Gonzalez et al., 2016). Crossley et al.  
146 (2020) and van Klink et al. (2020), on the other hand, were taxonomically selective when reporting their  
147 conclusions: both sets of authors included non-insect groups in their analyses, but restricted their  
148 conclusions (and paper titles) to insects (Desquilbet et al., 2021, 2020). Other studies of insect trends  
149 have been criticised with regards to whether particular modelling approaches have appropriately dealt  
150 with temporal biases in the data. For example, both Lister and Garcia (2018) and Soroye et al. (2020)  
151 have been criticised in this regard (Anon., 2020; Guzman et al., 2021; Willig et al., 2019). This brief  
152 overview of some recent disagreements highlights a fundamental problem: potential biases are rarely  
153 communicated to the reader in sufficient detail; instead, they are often addressed with a passing  
154 comment, if at all.

155 In other disciplines, strategies have developed to assist researchers in avoiding potentially inappropriate  
156 inferential claims. In medicine and related areas, inclusion of a study in a systematic review often  
157 requires that the original publication is subject to a “risk-of-bias” (RoB) assessment. Several tools have  
158 been developed to conduct RoB assessments, each focusing on a particular type of study and data (see  
159 **supplementary material 5**). Whilst many of these tools were designed for use in systematic reviews,  
160 others were designed for use at the primary research stage, or both (**supplementary material 5**).  
161 Regardless, the function of these tools is essentially the same: to clearly expose threats to the validity of  
162 a study’s conclusions arising from potential biases in the underlying data. RoB tools in medicine have

163 been described as reflecting a “shift in focus from methodological quality to risk of bias” (Sterne et al.,  
164 2016)—a shift that has yet to take place in ecology, despite efforts to provide structured approaches to  
165 documenting methodological choices in some areas (e.g. Grimm et al., 2010). It is easy to appreciate  
166 why this shift was needed in medicine: one would not want to approve some pharmaceutical product  
167 which had only been demonstrated to be safe in some population subset, for example. We argue that  
168 the increasing policy relevance of inferences about trends in biodiversity necessitates a similar transition  
169 in ecology.

170 In this paper we introduce ROBITT, a tool for assessing the “Risk-Of-Bias In studies of Temporal Trends in  
171 ecology”. The tool has a similar format to its counterparts in other fields: it comprises a number of  
172 “signalling” questions (Sterne et al., 2016) designed to elicit information on the potential for bias in a  
173 study. Users are first asked to define the statistical target population about which they intend to make  
174 inferences, and then to assess whether their data are likely to be representative of this population in the  
175 geographic, temporal, environmental, and taxonomic domains as relevant (the latter defined broadly as  
176 covering any organismal space that might be important for inference). If the data are found to be  
177 potentially biased, then the user is asked to explain how they will mitigate those biases, or how they will  
178 be clearly and appropriately communicated. Below we describe the development of the tool, provide an  
179 overview, describe its sections, and refer the reader to the supplementary material for the tool itself, a  
180 guidance document, and worked example. Finally, we discuss the potential value of ROBITT for ecology,  
181 and propose its inclusion as supplementary information for all studies of biodiversity trends based on  
182 species occurrence data—particularly where those data are obtained from aggregated databases.

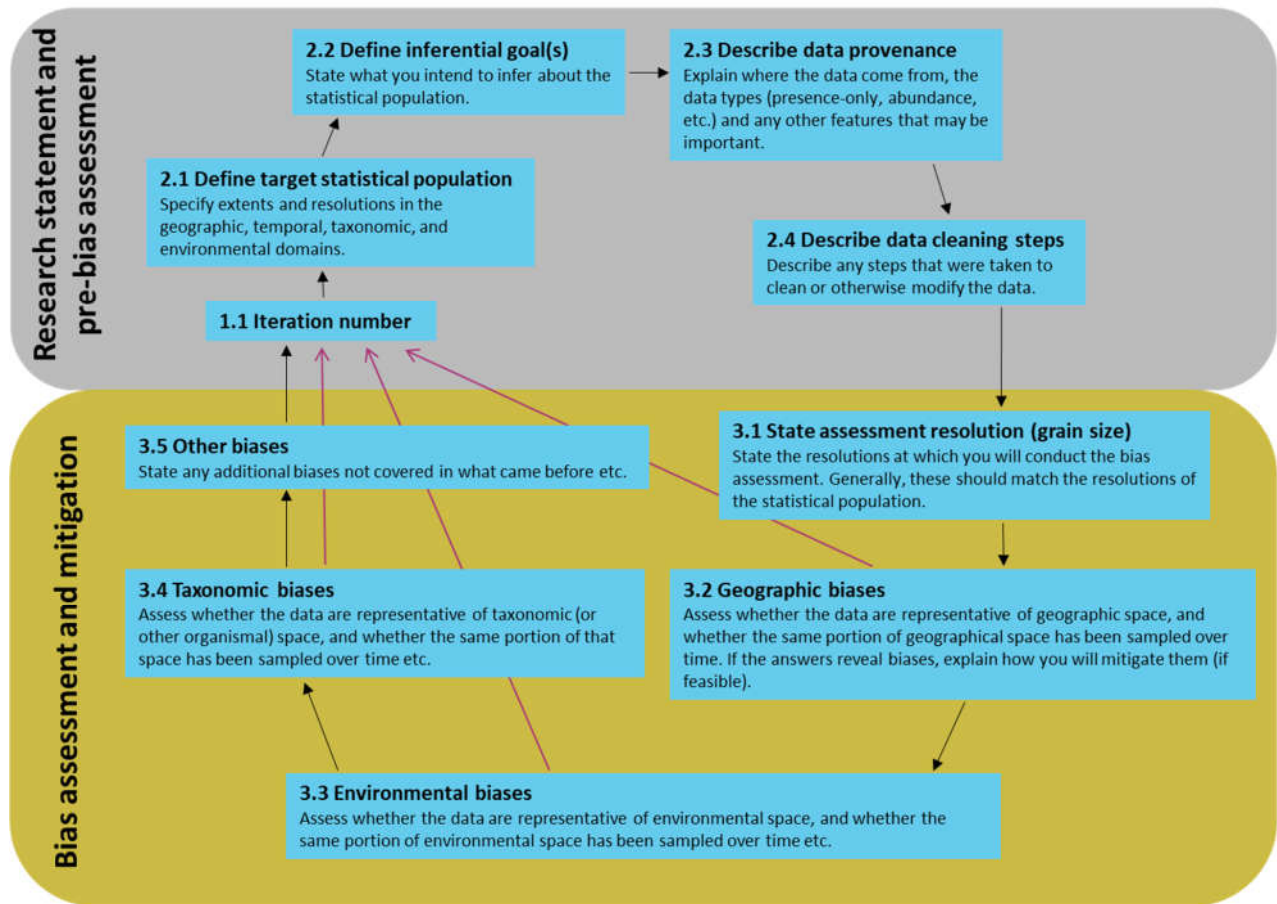
## 183 **ROBITT tool**

### 184 **Development**

185 ROBITT was developed through a consensus-forming process involving experts across relevant areas of  
186 ecology and evidence synthesis (the authors). See supplementary material **3** for details.

### 187 **Overview**

188 ROBITT comprises 17 questions designed to elicit information on a study’s potential for bias. The user  
189 may answer the questions using text and/or figures. The first section, the “research statement and pre-  
190 bias assessment”, comprises four questions concerning the scope of the research and related issues; the  
191 remainder constitutes the bias assessment itself. See Figure 1 for an overview of the tool. The ROBITT  
192 tool and supporting guidance document can be found in supplementary materials **1 and 2**. The guidance  
193 follows the PRISMA model (Page et al., 2021b): i.e., an explanation of the rationale for each question is  
194 given, followed by a summary of the expected response. Worked examples of ROBITT are provided in  
195 supplementary material **4**.



196

197 **Figure 1.** A conceptual overview of ROBITT with brief details about what is required at each stage. Black  
 198 arrows indicate the order in which users should proceed through a ROBITT assessment. Purple arrows  
 199 are used to indicate that completing a ROBITT form can be an iterative process: if the data are found to  
 200 be unrepresentative of any domain, then it may be necessary to return to step 1.1 and redefine the  
 201 extent and/or resolution of the statistical population accordingly.

## 202 **Tool sections**

### 203 ***Research statement and pre-bias assessment***

204 The purpose of this section is to assemble the information needed to assess a study's risk of bias. The  
 205 first step is to define the target population about which inferences are desired. This must include a  
 206 specification of the extents of any relevant domains (e.g. geographic, temporal, taxonomic,  
 207 environmental). It must also include a statement of the resolutions at which analyses will be conducted  
 208 (e.g., 1 km grid cells, annual increments etc.). This is important because the scale at which a research  
 209 question is formulated can influence data availability and the nature of, and potential for, biases (e.g.  
 210 Pescott et al., 2019). The next step is to state the inferential goal; for example, "to estimate temporal  
 211 trends in species' occupancy". In the remainder of this section, the user must document data  
 212 provenances, and explain and justify any steps that were taken to modify or clean data.

### 213 ***Bias assessment***

214 The main section of ROBITT is the bias assessment. This begins with a specification of the geographic,  
215 temporal, and taxonomic resolutions (grain sizes) at which the assessment will be conducted. Generally,  
216 these should match the resolutions at which inferences are desired (as specified in the research  
217 statement section). It would likely be inappropriate, for example, to assess data in decadal time periods  
218 and 100 km grid cells, and then conclude that they were unbiased for making yearly inferences at the 1  
219 km resolution. We note that there may be limited exceptions to this: for example, it is not possible to  
220 assess sampling biases at the species level using presence-only data because these say nothing about  
221 sampling effort where the focal species was not observed.

222 The next three subsections denote our three main domains of potential bias: geographic, environmental  
223 and taxonomic (or other organismal axis, such as functional group). Temporal biases are dealt with  
224 within each of these three sections (see below). In each subsection, the user must answer three  
225 questions: the first two are designed to reveal potential biases relative to the research question (i.e. the  
226 inferential goal). The first asks whether the data are representative of that domain; that is to say, do the  
227 data cover the whole domain evenly (ideally randomly)? The second question asks whether the same  
228 portion of the focal domain has been sampled over time; that is, is there any indication of temporal  
229 changes in coverage? The answers to this second question are crucial for assessing the suitability of the  
230 data for estimating temporal trends. To illustrate this, imagine that species data are collected from one  
231 location in one time period, and then from another in the next. Using these data to estimate changes in  
232 species' distributions or abundances between time periods will likely be problematic, because shifts in  
233 space are confounded with shifts in time. In one sense, the distinction between the first and second  
234 question can be considered equivalent to the distinction between external and internal validity: a study  
235 might have low external validity if it is not representative of some domain overall; however, for a subset  
236 of that domain (e.g. a well-sampled portion of geographic space), the data might be very informative  
237 about change (i.e. high internal validity). The answers to these first two questions in each domain have  
238 important implications for how one answers the third.

239 The third question in each domain subsection asks the user to state how they will mitigate potential  
240 biases indicated by the preceding two questions. There are several ways in which one might go about  
241 mitigating biases, which we review in the Discussion. There will be cases in which it is unnecessary to  
242 mitigate for a lack of coverage or inconsistent sampling over time, because these are not relevant to the  
243 inferential goal. For example, even coverage in environmental space may be inappropriate if  
244 environmental change is expected over time for the geographic extent of the analysis. Users are not  
245 required to explain poor coverage in any domain if it is irrelevant to their inferences. There could also be  
246 situations in which a bias is deemed relevant but mitigation is not feasible. In this case the resultant  
247 trends should be appropriately and clearly caveated.

248 The final subsection is "Other potential biases". This is different to the previous three in that it does not  
249 relate to a single domain; rather, it provides an opportunity for the user to consider additional biases  
250 that might affect their research. The first question asks whether there are any temporal biases that do  
251 not relate to the ecological states of interest. Often these biases will relate to observation error or the  
252 estimation of some parameter in a model related to this. For example, site-occupancy models are  
253 sometimes used to estimate trends in species' occupancies (Kéry and Royle, 2016). These models  
254 normally require data from replicate visits to sites within short spaces of time to estimate detection  
255 probabilities (thus correcting for imperfect detection). Where these models are used, analysts should



256 consider whether there is variation in the quantity and type of repeat visits that could result in biased  
257 estimates of these parameters (Royle, 2006).

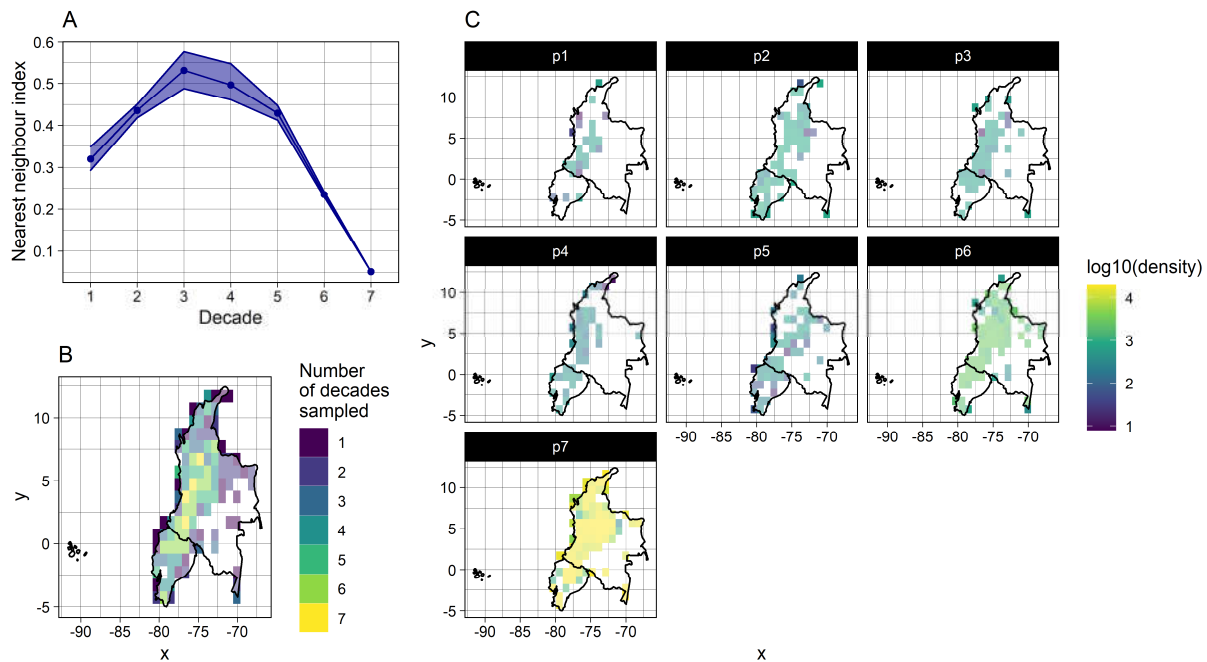
258 The second question in the “other biases” section asks the user to consider whether there are any other  
259 biases not covered by the preceding questions. Examples include biases relating to phenology, such as a  
260 mismatch between sampling dates and a species’ flight period; temporal baselines; and changes in the  
261 portion of one domain that has been sampled over some other domain, such as geographic variation in  
262 taxonomic coverage. Like earlier sections, the final question asks users to explain how they plan to  
263 mitigate biases revealed in their answers to the two preceding questions. See the guidance document in  
264 supplementary material 2 for detail on the expected content of responses to the ROBITT questions and  
265 other background information.

## 266 **Completing the assessment**

267 Whilst the assessment questions require individual answers, it may be that researchers prefer to provide  
268 responses in the main text of a report. As a point of comparison, PRISMA (Page et al., 2021a) provides a  
269 checklist format that allows researchers to direct the reader to the answer to any given question. This  
270 could also be the case here; for example, paper subheadings could be provided in response to a  
271 question, provided the text referenced was a complete answer to it.

272

273 Users may go about answering the questions in the bias assessment section in the best ways they see fit.  
274 However, we have found the use of “heuristics” that indicate the potential for bias to be of value. We  
275 use the term “heuristic” to acknowledge that it is generally not possible to determine the exact extent of  
276 bias without a probability sample for comparison. Many heuristics have been used to screen biodiversity  
277 data for biases in the literature; we briefly review these in Table 1 in supplementary material 2. The  
278 most common example is a map of the density of records across geographic space; such maps could  
279 provide evidence of geographic representativeness (or lack thereof). Taking this further, one could  
280 produce several maps, each pertaining to some time period; these could be used to assess temporal  
281 variation in geographic coverage. To obtain a more formal, quasi-statistical measure of geographic  
282 representativeness, one could compare the nearest neighbor distances of their data to those of a  
283 simulated random distribution (Clark and Evans, 1954). This gives an index indicating the extent to which  
284 the data depart from a random distribution geographically. In Figure 2 we present three example  
285 heuristics that could be used to screen data for geographic biases. In these examples, the heuristics are  
286 applied to hummingbird (Trochilidae) records collected between 1950 and 2019 in Ecuador and  
287 Colombia. Whilst heuristics of this type will be useful, it is important to remember that a ROBITT  
288 assessment is not intended to be a contextless set of numbers or figures: bias can strictly only be  
289 defined in relation to some inferential goal. The central point of ROBITT is that assessments of bias are  
290 clearly linked to a research question, and assessed in the context of this and any analytical tools being  
291 used to answer that question.



292

293 Figure 2. Three “heuristics” indicating the potential for geographic biases in data on hummingbird  
 294 occurrences collected in Ecuador and Colombia from 1950-2019. These data were downloaded from  
 295 GBIF (see supplementary material 3 for full details of the provenance of these data). In these examples,  
 296 the data are assessed in seven decadal time periods (p1 = 1950-1959, p2 = 1960-1969, etc.) and in 1°  
 297 grid cells. Panel A shows the nearest neighbor index for each decade; values further from one indicate a  
 298 greater departure from a simulated random distribution. The shaded band denotes uncertainty derived  
 299 by bootstrapping. Panel B is a map showing the number of decades in which records are available for  
 300 each grid cell. This is a simple measure of how the spatial distribution of sampling has changed over  
 301 time. Panel C shows the density of records in each grid cell for each decade on a log10 scale.

302 In some cases completing a ROBITT assessment will be an iterative process. For example, researchers  
 303 might complete a first iteration of the tool and find that data coverage is not sufficient in portions of  
 304 their geographic domain of interest. In this case, they might decide to redefine this domain to exclude  
 305 poorly sampled regions; this would mean completing a second iteration of ROBITT using an appropriate  
 306 subset (Fig. 1, see supplementary material 4). Where a ROBITT assessment is iterative, the user should  
 307 clearly version control (i.e. track and record changes over time) their documents and provide this history  
 308 as supporting information to their work.

## 309 Discussion

310 Sampling biases have long been recognised as a challenge for inference in ecology (e.g. Peters, 1991),  
 311 however, unlike in other disciplines, no formal tools for assessing these have been produced. We have  
 312 designed and introduced ROBITT, a tool for assessing the potential “Risk-Of-Bias in studies of Temporal  
 313 Trends in ecology”. The tool comprises a number of questions, each designed to clearly elicit the  
 314 potential for bias in the study under assessment. In answering these, users will define their research

315 question and target population across relevant domains, and then assess the degree to which their data  
316 are likely to be representative of these. We propose that researchers be strongly encouraged to include  
317 a ROBITT assessment as supporting information when publishing studies of temporal trends in  
318 biodiversity, especially when using aggregated data. We expect that this will support scientists in writing  
319 clear methods sections, strengthen evidence-based policy and practice, help resolve scientific  
320 controversies around biodiversity trends, assist editors, reviewers, and readers, and, ultimately,  
321 highlight the uncertainty associated with our understanding of ecological reality. Accumulated over  
322 studies, ROBITT assessments will also highlight where data are required to address pressing questions  
323 concerning biodiversity change.

324 We hope that the completion of ROBITT will become a standard requirement where researchers  
325 estimate trends from aggregated species occurrence data. The tools listed in **supplementary material 5**  
326 have set similar precedents in other disciplines; many are endorsed by journals and uptake is generally  
327 high. Whilst some reporting tools for various subdisciplines of ecology already exist, they do not focus  
328 on risk-of-bias. These include the ODD (Grimm et al., 2010, 2006) and TRACE (Schmolke et al., 2010)  
329 protocols for describing and documenting individual-based models, and the ODMAP (Zurell et al., 2020)  
330 protocol for documenting the use of species distribution models. In medicine, some reporting tools have  
331 evolved from a general focus on methodology to a more specific, and arguably more in-depth, focus on  
332 the impacts of bias on inference (Sterne et al., 2016). There is no doubt a place for both in ecology  
333 (indeed, some tools in medicine combine these aspects, e.g. Page et al., 2021a), however, we agree with  
334 Sterne et al. (2016) that in-depth, qualitative, assessments of risk-of-bias across relevant domains are  
335 more useful and revealing than simply checking methodological items off a list.

336 We suggest that researchers will get the greatest benefit from our tool if they use it to structure their  
337 research. ROBITT contains questions that researchers should be asking themselves already; indeed, it  
338 provides an opportunity to demonstrate the large amount of work that goes into studies of temporal  
339 trends in biodiversity, but which may go unreported. An interesting possibility is that ROBITT  
340 assessments could be supplied as part of the preregistration process, which is becoming increasingly  
341 common in ecology (e.g.,  
342 [https://besjournals.onlinelibrary.wiley.com/hub/journal/26888319/registered-reports-author-](https://besjournals.onlinelibrary.wiley.com/hub/journal/26888319/registered-reports-author-guidelines)  
343 [guidelines](https://besjournals.onlinelibrary.wiley.com/hub/journal/26888319/registered-reports-author-guidelines)). If, on the other hand, a ROBITT form is completed just before the submission of an article  
344 for publication, then it may reveal problems that could have been dealt with earlier. Completing the  
345 form during the research process has the potential to save researchers' time, by providing a framework  
346 for structuring thought and decision-making.

347 Much of the risk-of-bias literature in other disciplines has focused on the effects of interventions (see  
348 supplementary material 5). In this type of research the questions asked are causal, because the desired  
349 inference concerns whether some action results in some outcome. This has also been the standard focus  
350 of evidence-based conservation (e.g. Lortie et al., 2015). ROBITT, on the other hand, is primarily focused  
351 on descriptive inference of the type that is often used for ecological indicators (e.g. Gregory et al., 2005)  
352 or the EBV literature (e.g. Jetz et al., 2019). However, this distinction is not absolute, and there are many  
353 examples of ecological studies that use aggregated species occurrence data in attempts to reach causal  
354 conclusions. For example, Woodcock et al. (2016) divided wild bee data for Britain into two subsets  
355 based on insecticide use, assessing trends in occupancy for taxa in each subset. Whilst this type of  
356 assessment is correlative, there is often a causal motivation (e.g. the title of Woodcock et al. 2016

357 implies causality). Whilst the ROBITT tool has not been explicitly designed to deal with these situations,  
358 we suggest that it will still be useful when attempting to make causal inferences from observational  
359 data. In the example of Woodcock et al. (2016), the domain representativeness of the data in the two  
360 subsets could have been assessed separately to investigate the potential for confounding; additionally,  
361 the full dataset could have been assessed for its external validity.

362 One key issue with risk-of-bias assessments is that, whilst it might be easy to define a target population,  
363 in some cases it will not be straightforward to determine whether any given sample is representative of  
364 that population. For example, a researcher might define their population as wild bees in Chile in the  
365 2010s. Mapping the data might reveal that available data are not randomly distributed across the  
366 country, but does this reflect the true distribution of wild bees in Chile, or does it reflect non-random  
367 sampling? The user might also want to establish whether they have data for all known species of wild  
368 bee in Chile: how do they know whether this is the case? The answers to these questions will vary.

369 Whilst it will not always be easy to establish whether a sample is representative of a population, we  
370 propose some simple criteria. First, subject-matter experts should be consulted; experts may be able to  
371 separate sampling biases from biological phenomena. For example, an expert might know, or suspect,  
372 that a species or taxon group occupies areas where it has not been recorded; this is likely to be a strong  
373 indication of sampling bias. Second, it might be possible to supplement expert advice with published  
374 information. Regional or national Floras etc. may list (undigitised) specimens, or provide information on  
375 regional occurrences at some coarse spatio-temporal level. Third, when using presence-only data for a  
376 reasonably large number of species in the same group (e.g., bees, birds), it may be acceptable to assume  
377 that the combined distribution of records for all species approximates the sampling distribution (Dudík  
378 et al., 2005; Phillips et al., 2009). In this case, the combined data would ideally be randomly distributed  
379 across the geographical domain. Fourth, presence/absence and abundance data may be a direct  
380 reflection of the distribution of sampling (i.e. a species might not be detected but a record is still made  
381 of the event), therefore such data may provide reliable information on the distribution of sampling in  
382 space and time. If the basis of sampling is known (e.g. random, systematic-random etc.), then data may  
383 be representative, at least within the bounds of the original survey. However, even here, such a sample  
384 may still be unrepresentative of an analyst's target population if that population pertains to a different  
385 spatio-temporal-taxonomic domain to the survey. We can see very few scenarios where it will not be  
386 possible to at least approximate the degree to which a dataset is representative of a given population  
387 using all the knowledge that could be brought to bear. Indeed, this is the rationale behind qualitative  
388 risk-of-bias tools based on expert assessments (supplementary material 5).

389 If analysts cannot reach an informed conclusion with regards to the likely representativeness of a  
390 sample, then broader inference is not likely to be meaningful; simple descriptive statistics could be used  
391 instead, and this limitation acknowledged, with paper titles, abstracts etc. all reflecting this. This may  
392 seem a negative conclusion for an analyst to reach, but we argue that this is likely to be the most  
393 honest, and scientific, endpoint for a dataset whose representativeness cannot be clearly assessed.

394 Four of the questions in ROBITT provide researchers with an opportunity to consider whether and how  
395 they can mitigate biases revealed elsewhere in the tool. It is not possible to review here all possible  
396 measures that could be taken by researchers; a full treatment of adjustments and models for dealing  
397 with bias would have to cover many topics within statistics and ecological data. However, we note three

398 general approaches. The first is to modify the data in some way (e.g. thinning; Inman et al. 2021). The  
 399 second is to model the biases; typically, this will involve incorporation of variables thought to capture  
 400 the biasing mechanism in some form of regression analysis (e.g. van Strien et al., 2019), although other  
 401 approaches are possible (Ahmad Suhaimi et al., 2021). Third, we suspect that in many cases ROBITT will  
 402 reveal the need to restrict the extent of researchers' inferences. This might include redefining the spatial  
 403 extent of an analysis to reflect the fact that data are scarcely available in some portion of geographic  
 404 space, or coarsening the temporal resolution to "smooth over" temporal biases in geographic or  
 405 taxonomic coverage (Pescott et al., 2019). Any modifications to the extents of the statistical population  
 406 should be reflected in paper titles, abstracts, etc. We note that it will often be prudent for researchers to  
 407 assess the sensitivity of their conclusions to the choice of bias mitigation strategy: some statistical  
 408 "fixes" can make aspects of inference worse (Gelman, 2007; Lele, 2010). Nevertheless, we suspect that  
 409 by using these general bias mitigation strategies, researchers will usually be able to proceed with their  
 410 analyses, even if those analyses relate to more limited statistical populations than initially envisioned.  
 411 The problem of inference from biased samples is difficult, and quick fixes do not exist. ROBITT  
 412 represents a first attempt to encourage more thoughtful assessment of the potential for bias to  
 413 undermine the robust estimation of temporal trends in ecology. We intend to update the tool over time  
 414 and welcome feedback from users.

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