

1 Exploratory and confirmatory conservation research in the
2 open science era

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13 Abstract:

- 14 1. Conservation biology is becoming a more open science, with an increasing focus on
15 large-scale assessments of the patterns and processes of biodiversity dynamics.
16 However, the new challenges arising when it comes to defining exploratory and
17 confirmatory research practices, has been so far overlooked. We discuss how the
18 research community could meet these new challenges by allowing full use of different of
19 scientific approaches, without blurring the distinction between exploration and
20 hypothesis-testing confirmatory research.
- 21 2. A rapid screening of a random selection of articles from the literature suggests that
22 neither experimental protocols nor hypothesis testing *sensu stricto* are common in
23 conservation biology. Most experiments are carried out on small spatial scales, which
24 contrast with current global policy processes and research trends towards large spatial
25 and temporal scales.
- 26 3. We suggest that a clearer distinction between exploratory and confirmatory research can
27 be achieved by reevaluating the important, but different, role that each plays in the
28 scientific process.
- 29 4. This clearer distinction could be facilitated by allocating journal sections to the different
30 types of research, embracing new tools offered by the open science era, such as pre-
31 registration of hypothesis, establishing new systems where posthoc hypothesis emerging
32 through exploration can also be registered for later testing, and more broad adoption of
33 causal inference methods that foster more structured establishment of hypotheses
34 about causal mechanisms.

35 5. To fully gain the benefits from the open science era, researchers, funding bodies and
36 journal editors should explicitly consider how incentives could encourage openness
37 about methods and approaches, and value the full plurality of scientific approaches.

38

39 Rigorous science in conservation biology

40 As a response to global biodiversity loss, conservation biology is increasingly focused on
41 detecting patterns of biodiversity change, isolating the factors that are causing this loss, and
42 ultimately suggesting mitigation measures or management solutions. Conservation biology
43 has inherited scientific tools and traditions from older sciences such as ecology and wildlife
44 management (Caughley 1994), but is at its core an applied, interdisciplinary and mission
45 driven science (Soulé 1996). Because biodiversity loss and ecosystem transformations are
46 expected to cause major challenges to present and future human societies (Millennium-
47 Ecosystem-Assessment 2005), the transparency and rigor of the science that underpins
48 policy and management decisions is decisive to the wellbeing of future generations of
49 humans.

50 Following some high-profile publications pointing towards a reproducibility crisis in fields like
51 psychology (Nosek & Collaboration 2015) and social research (Camerer *et al.* 2018), there
52 has been much focus on repeatability and reproducibility of scientific results (see e.g. the
53 news feature in Nature by Baker 2016). One of the consequences of this renewed focus is
54 the global focus on FAIR data management and open sharing of research data (Wilkinson *et*
55 *al.* 2016), software and code used to perform statistical analysis. These changes are all parts
56 of a more general movement towards “open science” (Nosek *et al.* 2015).

57 Increasing accessibility of new data sources allows researchers to apply a wide range of
58 models to data for exploratory science. This contrast with the pleas for more widespread
59 adoption of confirmatory research where hypotheses are described a-priori and then
60 carefully tested based on empirical data (Caughley 1994; Houlahan *et al.* 2017). A rapid
61 screening of a sample from the conservation literature (**Box 1**) suggest that conservation

62 biology researchers often do not follow the strong inference paradigm (Platt 1964; Sells *et*
63 *al.* 2018), nor do they follow the hypothetico-deductive method. Our rapid screening of the
64 literature also suggests that large scale studies often have large impacts if measured through
65 citation rates (**Box 1**). Here, we discuss how both exploratory and confirmatory research is
66 needed in the field of conservation biology, how we can improve understanding in the open
67 science era, and how both scientists and journal editors should assist in the task of extracting
68 the maximum value from different scientific approaches without blurring the distinction
69 between exploration and confirmation.

70

71 [A mature research community should value both exploration and confirmation](#)

72 Many earlier authors, including Caughley (1994), Sells *et al.* (2018) and Betini, Avgar and
73 Fryxell (2017), have called for more formal use of the hypothetico-deductive method and the
74 strong inference paradigm (*sensu* Platt 1964) within conservation biology and wildlife
75 management. We agree with that plea, but also underline the fundamental role that
76 descriptive studies documenting the state or trends of local or global biodiversity, or the
77 natural history of species, has for conservation biology (Beissinger & Peery 2007; Pereira *et*
78 *al.* 2013; Lehtikoinen *et al.* 2019). Recently, the emergence of Essential Biodiversity Variables
79 (EBV) emphasises that robust descriptive research combined with observational data is still
80 fundamental to our scientific progress (Pereira *et al.* 2013). Moreover, the developments of
81 the United Nation's Sustainability Goals (SDG) and a movement towards more planetary
82 scale assessments, such as those carried out by the Intergovernmental Panel on Biodiversity
83 and Ecosystem Services (IPBES), makes it unfeasible for policy to rely mainly on insights
84 gained from experimental research (Mazor *et al.* 2018; Box 1).

85 Nevertheless, to avoid an ever-growing list of un-tested hypothesis emerging from
86 exploratory research, we must also reevaluate the fundamental (but different) role that
87 hypothesis-testing and prediction play in conservation biology research (Houlahan *et al.*
88 2017). Only by testing a-priori articulated hypothesis can we robustly confirm or reject the
89 potential of a scientific hypothesis to describe natural phenomena. However, studies do not
90 always follow such protocols and surveys have revealed the existence of a number of
91 questionable research practices (Ioannidis *et al.* 2014; Fraser *et al.* 2018). Such practices
92 include both “*harking*” (Hypothesis After Results Are Known), where ad-hoc postdictions are
93 presented as if they were already planned before the study was conducted, and “*p-hacking*”
94 where researchers carelessly search for significant associations in the data (and often
95 present them as if they were from a-priori hypotheses). Recent surveys suggest that they
96 might be common also among ecologists and evolutionary biologists (Fraser *et al.* 2018).
97 Without more frequent use of prediction, we risk that confirmation bias and the personal
98 beliefs of the scientists will result in overly self-confident ‘storytelling’ with weak scientific
99 support (Hayward *et al.* 2019). Basing conservation planning and mitigation actions on such
100 research may lead to costly mis-management.

101

102 [Novel ways to test ecological theories](#)

103 Our survey of the literature (**Box 1**) (see also Betini, Avgar & Fryxell 2017; Sells *et al.* 2018)
104 suggest that conservation biology research most often does not confirm to strict hypothesis
105 testing. In the open science era, there are ample possibilities to increase the use and impact
106 of confirmatory research, by more widely embracing new tools and methods, and especially
107 increased data availability.

108 Strict experiments in conservation biology (**Box 1**) are generally conducted at small local
109 spatial scales (although there are some very notable exceptions, e.g. Krebs, Boutin & Boonstra
110 1995; Wiik *et al.* 2019). This contrasts with the fact that many ecological and policy
111 processes operate at far larger scales (Estes *et al.* 2018). Better utilization of large-scale
112 unreplicated natural experiments could facilitate an improved understanding of causal
113 relationships in ecological systems (Barley & Meeuwig 2017; Serrouya *et al.* 2019), especially
114 the impacts of rare and extreme events (e.g. Gaillard *et al.* 2003). A complementary
115 approach, when experiments are not feasible, would be to apply methods that allow
116 integration of findings from small-scale manipulative experiments into large-scale synthesis
117 of drivers of biodiversity change. Such integration will necessitate closer collaboration
118 between ecologists working on different spatial scales, and between experimentalists and
119 modellers (Heuschele *et al.* 2017). The increased popularity of hierarchical statistical models
120 and methods to integrate data from disparate data sources (Nilsen & Strand 2018; Miller *et*
121 *al.* 2019) facilitate such an integration. In the new era of open science, large amounts of
122 data from both field surveys and experiments are now becoming available making such
123 integration much more feasible.

124 Given our reliance on observational data, conservation biology research could gain more
125 insight into causal processes by more widely applying novel statistical methods that are seek
126 to establish causality from observational data (Law *et al.* 2017). A side effect of adopting
127 causal inference approaches is forcing researchers to think more deeply about the direct and
128 indirect relationships of variables in their study systems (Ferraro, Sanchirico & Smith 2019).
129 Causal inference methods aiming at controlling for confounding factors include matching (to
130 control observable confounders) and use of panel data and synthetic controls to control for
131 unobservable confounders, as well as instrumental variables to eliminate unobservable

132 confounders (reviewed by Law *et al.* 2017), and time series methods such as convergent
133 cross mapping (Sugihara *et al.* 2012). Time-series data might be particularly useful because
134 they are unidirectional implying that cause must precede effect (Dornelas *et al.* 2013).
135 Triangulation, whereby several approaches are formally applied to the same problem, could
136 serve as another model for increasing the reliability of causal claims (Munafo & Smith 2018).
137 Finally, to effectively synthesize evidence from causal claims across studies, a wider adoption
138 of systematic reviews and other structured evidence synthesis methods would allow more
139 robust assessment of the evidence base (Pullin & Stewart 2006). In the open science era, the
140 time is now ripe to develop models and procedures that conduct evidence synthesis based
141 directly on open data rather than published effect sizes (Culina *et al.* 2018).

142

143 [Journals, editors, and reviewers should assist in the change](#)

144 Science is not conducted in isolation in research labs, but rather represents a collective social
145 endeavour involving many people with different roles to fill. Journals could play an
146 important role facilitating scientific rigor of the studies that underpin real-life conservation
147 decisions. This could partly be achieved by creating new incentives for more honest and
148 open reporting from the research process.

149 Pre-registration of research hypothesis has been advocated (Nosek *et al.* 2018), partly to
150 distinguish exploration and confirmation research. In the open science era, studies are
151 increasingly based on pre-existing data, and even data that have been previously analysed
152 and with results published in a scientific journal. This should however not discourage *a priori*
153 hypothesis development and pre-registration (Nosek *et al.* 2018). Journal editors could
154 facilitate this shift by applying a model where authors declare their study design and identify

155 at which stage in the process they developed their hypothesis (e.g. before or after data
156 collection, before or after initial data analysis etc). This could include a link to the pre-
157 registered hypothesis that might be hosted on e.g. Open Science Framework (www.osf.io),
158 and potentially an associated “open science badge” (Kidwell *et al.* 2016) as a sign of an open
159 research practice.

160 We also encourage journal editors to more actively encourage fair valuation of case studies
161 that mainly describe and document the state of local and global biodiversity. To
162 accommodate this, we suggest that journals should more explicitly allocate different
163 sections to different types of studies (exploratory, methods, confirmatory/hypothesis testing
164 etc). This will make the publication process more transparent and facilitate more honest
165 reporting of how the study was performed, especially reducing the incentives for *harking*,
166 and lessen publication bias towards significant studies.

167 Finally, we propose (as a counterpart to pre-registration of hypotheses) a model where
168 hypotheses arising from explicit exploratory research could also be registered so that they are
169 readily available for testing in subsequent studies. Given the rise of global databases and
170 repositories, such a model could make it feasible to track hypothesis to their source, which
171 would allow for fair attribution of credit to those that originally proposed the hypothesis,
172 and it would provide a clearer link between exploratory (hypothesis generating) and
173 confirmatory (hypothesis testing) research.

174

175 Outlook

176 We should value the unique contributions of exploratory and confirmatory studies, but be
177 much clearer about the fundamental differences between them. In the open science era

178 (Nosek *et al.* 2015), where more and more research is based on pre-existing (and often
179 open) data, and where large scale studies are needed to address key conservation policy
180 challenges, a simple plea to follow the strong inference paradigm (Platt 1964) might not be
181 sufficient. However, current incentives that promote the presentation of studies that are by
182 design and conduct exploratory as if they were confirmatory is a disservice to scientific
183 progress. In applied fields like conservation biology, this will also delay progress to solve real
184 conservation problems. The open science era has already radically improved the
185 reproducibility of research; however, we argue that a cultural shift, involving researchers,
186 journals, and funding bodies, is still needed towards full transparency and valuation of
187 diverse research methods.

188

189

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193 of Norway.

194

195 **Data accessibility:** Data and R-scripts used to perform the randomization routines and
196 produce figures for Box 1 is currently available here: <https://osf.io/n8fum/>

197

198 **Authors contributions:** EBN conceived the idea for this work, after discussions with DB and
199 JDCL. EBN and DB performed the literature survey for Box 1. EBN were responsible for
200 writing the manuscript, with inputs from JDCL and DB. All authors edited and approved the
201 final version of the manuscript.

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313 Box 1: State of conservation biology as a science

314 In a seminal paper from 1994, G. Caughley (Caughley 1994) was concerned that parts of
315 conservation biology (the branch concerned with declining populations) had a very thin
316 theoretical basis, was carried out mainly as a series of case studies, and therefore often had
317 limited generalisable value. In line with many other philosophers of science, Caughley
318 suggested that much more rapid progress would be made if conservation biologists applied
319 the strong inference paradigm (sensu Platt 1964) when designing and conducting research.

320 To gain a rapid insight into the current state of affairs in the scientific conservation
321 literature, we randomly sampled 159 papers published in eight journals covering
322 conservation biology, applied ecology and wildlife management. We only included studies
323 from terrestrial ecology, that were data-driven (i.e. not reviews or pure simulation studies),
324 that presented the results from at least one statistical test, that presented original data or
325 data from literature surveys, and focused on conservation biology. From these studies, we
326 assessed i) to which extent one or more clearly stated hypotheses were presented in the
327 introduction, ii) whether there were multiple competing hypothesis and, iii) whether they
328 applied an experimental study design. In addition, we extracted the number of citations
329 registered by Web of Science. A more comprehensive description of the inclusion criteria
330 and data extraction procedures can be found in **Appendix S1**.

331 Based on our sample of research papers, it seems that clearly stating a research hypothesis
332 in the introduction is surprisingly rare in the literature (**Fig 1a**). Overall, only about 19% of
333 the studies presented clear hypothesis, whereas about 26% presented what we term
334 “implied hypotheses” or “partly”, where the hypothesis could be inferred from the text but
335 was not presented clearly. After removing articles mainly focusing on methods development,

336 the corresponding proportions were 23% (clear hypothesis) and 28% (implied), respectively.
337 Presenting multiple competing hypothesis, as described in the original presentation of the
338 strong inference paradigm (Platt 1964) is even rarer, and only 2 of the studies we reviewed.
339 Another hallmark of science is the use of well planned, randomized and replicated
340 experimental manipulation to test for causal relationships (Platt 1964; Caughley 1994).
341 Based on our review, however, the use of full experimental designs are rare, and only 12% of
342 the studies we reviewed were based on randomized controlled experimental designs. In
343 addition, 15% of the studies in our sample included Before-After-Control-Impact (BACI) or
344 Quasi-experimental protocols. The majority of the randomized controlled experiments were
345 performed on a local spatial scale (**Fig 1b**), although a few studies presented landscape scale
346 experiments. In our sample, local scale studies in general received less attention in the
347 literature compared to studies spanning larges spatial scales (**Fig 1b**).

348

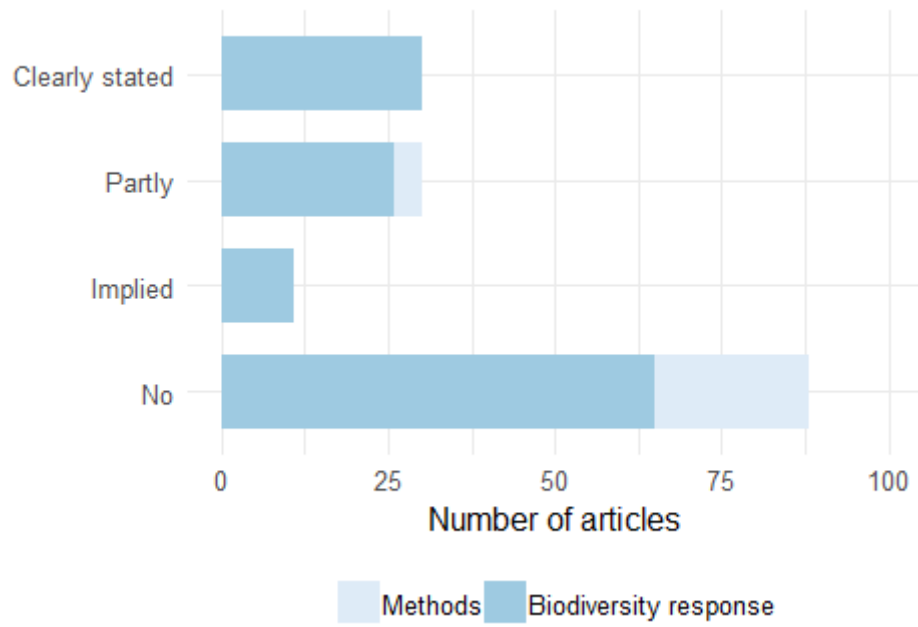
349 Figure Legends

350 **Figure 1.** In **a)** the proportion of articles that reported clear hypotheses, implied or partly indicated
351 hypotheses that were tested, and articles that did not present hypotheses. In **b)** the proportion of
352 articles that used experimental, quasi-experimental/BACI or no experimental designs are matched
353 with the corresponding spatial scales of the studies. The size of the circles indicates the number of
354 studies. The colour key indicates citation rates (mean annual number of citations since the year of
355 publication).

356

357 Figures

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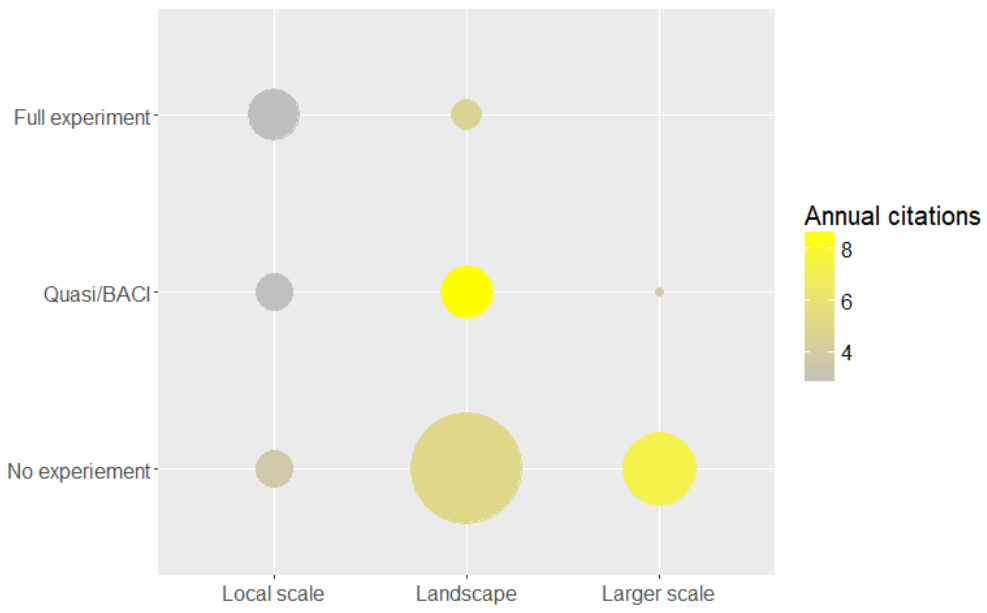
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360 **Fig 1a**

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365 **Fig 1b**