

1 Exploratory and confirmatory research in the open science era

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16 Abstract:

- 17 1. Applied ecological research is increasingly becoming a part of the Open Science
18 movement. However, new challenges about how we define our science when
19 biodiversity data is increasingly being shared and re-used are not solved. Among these
20 challenges is the risk associated with blurring the distinction between research that
21 mainly seeks to explore patterns with no *a-priori* articulated hypotheses (*exploratory*
22 *research*), and research that explicitly tests *a-priori* formulated hypotheses (*confirmatory*
23 *research*).
- 24 2. A rapid screening of a random selection of peer-reviewed articles suggests that neither
25 experimental protocols nor hypothesis-testing *sensu stricto* are common in applied
26 ecological research. In addition, most experiments are carried out on small spatial scales,
27 which contrast with current global policy needs and research trends towards addressing
28 large spatial and temporal scales.
- 29 3. To solve fundamental local, regional and global societal challenges, we need both
30 exploratory and confirmatory research; however, there is an urgent need to more clearly
31 distinguish the two. This will require a reevaluation of the important, but different, roles
32 that each play in the scientific process.
- 33 4. A clearer distinction could be facilitated by allocating journal sections to different types
34 of research; embracing new tools offered by the open science era, such as pre-
35 registration of hypothesis; establishing new systems where *post-hoc* hypotheses
36 emerging through exploration can also be registered for later testing; and more broad
37 adoption of causal inference methods that foster more structured testing of hypotheses
38 about causal mechanisms from observational biodiversity data.

39 5. To gain the full benefits from the open science era, researchers, funding bodies and
40 journal editors should explicitly consider incentives that encourage openness about
41 methods and approaches, as well as value the full plurality of scientific approaches
42 needed to address questions in conservation science.

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44

45 Rigorous science in applied ecology

46 As a response to global biodiversity loss, conservation science and applied ecological
47 research is increasingly focused on detecting patterns of biodiversity change, isolating the
48 factors that are causing this loss, and ultimately suggesting mitigation measures or
49 management solutions (Kareiva & Marvier 2012). Because biodiversity loss and ecosystem
50 transformations are expected to cause major challenges to present and future human
51 societies (IPBES 2019), the rigor of the science that underpins policy and management
52 decisions is decisive to the wellbeing of future generations of humans and the fate of our
53 planet's biodiversity. Following some high-profile publications pointing towards a
54 reproducibility crisis in fields such as psychology (Nosek & Collaboration 2015) and social
55 sciences (Camerer *et al.* 2018), there is currently much focus in scholarly publications on the
56 repeatability and reproducibility of scientific results (see e.g. the news feature in Nature by
57 Baker 2016). Applied ecological research is not immune to these challenges, but so far the
58 discussion has not been high on the agenda within this field. One key aspect of the
59 discussion about scientific rigor (Nosek *et al.* 2018) is a reevaluation of the distinction
60 between research that mainly seeks to explore patterns in the data (hereafter *exploratory*
61 *research*) and research that tests scientific hypotheses that are clearly stated before the
62 study is conducted (hereafter *confirmatory research*).

63 In the philosophy of science, this distinction has been extensively discussed, and following
64 the classical paper by Platt (1964) on strong inference the importance of confirmatory
65 research has been long appreciated. Also within conservation science and applied ecology,
66 several authors (including Caughley 1994; Betini, Avgar & Fryxell 2017; Sells *et al.* 2018) have
67 called for more formal use of confirmatory research and application of the strong inference

68 paradigm (sensu Platt 1964). However, a rapid screening of a sample from the applied
69 ecological literature (**Box 1**) suggests that most researchers within this field do not follow
70 the strong inference paradigm (Platt 1964; Sells *et al.* 2018), nor do they rely on clearly
71 stated *a-priori* hypotheses that are tested with empirical data.

72 Here, we discuss how both exploratory and confirmatory research is needed in applied
73 ecological research, and how both scientists and journal editors should assist in the task of
74 extracting the maximum value from different scientific approaches without blurring the
75 distinction between exploration and confirmation.

76

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

78 One consequence of a general movement towards “open science” (Nosek *et al.* 2015) is the
79 focus on open sharing of research data (Wilkinson *et al.* 2016). Increasing accessibility of
80 new data sources allows researchers to apply an ever-widening range of models to data for
81 exploratory science. This contrast with the pleas for more widespread adoption of
82 confirmatory research where hypotheses are described *a-priori* and then carefully tested
83 based on empirical data collected specifically for that purpose (Caughley 1994; Houlahan *et*
84 *al.* 2017). We agree with that plea for more formal testing of scientific hypotheses in applied
85 ecological research, but also underline the fundamental role that descriptive studies
86 documenting the state or trends of local, regional or global biodiversity, or the natural
87 history of species, has for conservation science (Beissinger & Peery 2007; Pereira *et al.*
88 2013). In addition, exploratory research plays a key role in generating new hypothesis that
89 could formally be tested later. Moreover, the development of the United Nation’s
90 Sustainable Development Goals (SDGs) and a movement towards more planetary scale

91 assessments, such as those carried out by the Intergovernmental Panel on Biodiversity and
92 Ecosystem Services (IPBES), makes it unfeasible for policy to rely mainly on insights gained
93 from experimental research (Mazor *et al.* 2018; Box 1). Our rapid screening of the literature
94 indeed suggests that large-scale studies often have large impacts, at least if measured
95 through citation rates (**Box 1**).

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

112 Novel ways to test ecological theories

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

118 Strict experiments in applied ecology (**Box 1**) are generally conducted at small spatial scales
119 (although there are some very notable exceptions, e.g. Krebs, Boutin & Boonstra 1995; Wiik *et*
120 *al.* 2019). This contrasts with the fact that many ecological and policy processes operate at
121 far larger scales (Estes *et al.* 2018). Better utilization of large-scale unreplicated natural
122 experiments could improve understanding of causal relationships in ecological systems
123 (Barley & Meeuwig 2017), especially the impacts of rare and extreme events (e.g. Gaillard *et*
124 *al.* 2003). A complementary approach, when experiments are not feasible, would be to apply
125 methods that allow integration of findings from small-scale manipulative experiments into
126 large-scale syntheses of drivers of biodiversity change. Such integration will necessitate
127 closer collaboration between ecologists working at different spatial scales, and between
128 experimentalists and modellers (Heuschele *et al.* 2017). The increased popularity of
129 hierarchical statistical models, especially integrated population models, which integrate data
130 from disparate data sources, could facilitate such an integration (Miller *et al.* 2019). In the
131 new era of open science, large amounts of data from both field surveys and experiments are
132 now becoming available, widening the range of opportunities for data integration.

133 Given our reliance on observational data, more insight into causal processes could be gained
134 by more widely applying novel statistical methods that seek to establish causality from

135 observational data (Law *et al.* 2017). Causal inference approaches force researchers to think
136 more deeply about the direct and indirect relationships of variables in their study systems
137 (Ferraro, Sanchirico & Smith 2019). These approaches include controlling for confounding
138 factors by matching (to control observable confounders) and use of panel data and synthetic
139 controls to control for unobservable confounders, as well as instrumental variables to
140 eliminate unobservable confounders (reviewed by Law *et al.* 2017), and time-series methods
141 such as convergent cross mapping (Sugihara *et al.* 2012). Time-series data might be
142 particularly useful because they are unidirectional - cause must precede effect (Dornelas *et*
143 *al.* 2013). Triangulation, whereby several approaches are formally applied to the same
144 problem, could serve as another model for increasing the reliability of causal claims (Munafo
145 & Smith 2018).

146 Finally, to effectively synthesize evidence from causal claims across studies, a wider adoption
147 of systematic reviews and other structured evidence synthesis methods would allow more
148 robust assessment of the evidence base (Pullin & Stewart 2006). In fact, in the open science
149 era, evidence synthesis can be performed directly on open data rather than published effect
150 sizes, increasing the range of questions that can be addressed (Culina *et al.* 2018).

151

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

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

158 Pre-registration of research hypothesis has been advocated (Nosek *et al.* 2018), partly to
159 distinguish exploration and confirmation research. In the open science era, studies are
160 increasingly based on pre-existing data, and even data that have been previously analysed
161 and with results published in a scientific journal. This should however not discourage *a priori*
162 hypothesis development and pre-registration (Nosek *et al.* 2018). Journal editors could
163 facilitate this shift by applying a model where authors declare their study design and identify
164 at which stage in the process they developed their hypothesis (e.g. before or after data
165 collection, before or after initial data analysis etc). This could include a link to the pre-
166 registered hypothesis that might be hosted on e.g. Open Science Framework (www.osf.io),
167 and potentially an associated “open science badge” (Kidwell *et al.* 2016) as a sign of an open
168 research practice.

169 We also encourage journal editors to more actively encourage fair valuation of empirical
170 case studies that mainly describe and document the state and trend of biodiversity. To
171 accommodate this, more journals could explicitly allocate different sections to different
172 types of studies (exploratory, methods, confirmatory/hypothesis testing etc). This will make
173 the publication process more transparent and facilitate more honest reporting of how the
174 study was performed, especially reducing the incentives for *harking*, and reduce publication
175 bias of significant studies.

176 Finally, we propose (as a counterpart to pre-registration of hypotheses) a model where
177 hypotheses rising from exploratory research could also be registered so that they are readily
178 available for testing in subsequent studies. Given the rise of global databases and
179 repositories, such a model could make it feasible to track hypotheses to their source, which
180 would allow for fair attribution of credit to those that originally proposed the hypothesis,

181 and it would provide a clearer link between exploratory (hypothesis generating) and
182 confirmatory (hypothesis testing) research.

183

184 Outlook

185 We should value the complimentary contributions of exploratory and confirmatory studies,
186 but be much clearer about the fundamental differences between them. In the open science
187 era (Nosek *et al.* 2015), where more and more research is based on pre-existing (and often
188 open) data, and where large-scale studies are needed to address key conservation policy
189 challenges, a simple plea to follow the strong inference paradigm (Platt 1964) might not be
190 sufficient. However, current incentives that promote the presentation of studies that are, by
191 design and conduct, exploratory as if they were confirmatory is a disservice to scientific
192 progress. In applied fields like conservation biology, this will also delay progress in solving
193 world problems. The open science era has already radically improved the reproducibility of
194 research; however, we argue that a cultural shift, involving researchers, journals, and
195 funding bodies, is still needed towards full transparency and valuation of the plurality of
196 research methods.

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198

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203

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

206

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

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311 Box 1: State of applied ecology as a science

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

324 Based on our sample of research papers, it seems that clearly stating a research hypothesis
325 in the introduction is surprisingly rare in the literature (**Fig 1a**). Overall, only about 19% of
326 the studies presented clear hypotheses, whereas about 26% presented what we term
327 “implied hypotheses” or “partly”, where the hypothesis could be inferred from the text but
328 was not presented clearly. After removing articles mainly focusing on methods development,
329 the corresponding proportions were 23% (explicit hypotheses) and 28% (implicit
330 hypotheses), respectively. Presenting multiple competing hypothesis, as described in the
331 original presentation of the strong inference paradigm (Platt 1964) is even rarer, and only
332 visible in 2 of the studies we reviewed.

333 Another hallmark of science is the use of well planned, randomized and replicated
334 experimental manipulation to test for causal relationships (Platt 1964; Caughley 1994).
335 Based on our review, however, the use of full experimental designs are rare, and only 12% of
336 the studies we reviewed were based on randomized controlled experimental designs. In
337 addition, 15% of the studies in our sample included Before-After-Control-Impact (BACI) or
338 Quasi-experimental protocols. The majority of the randomized controlled experiments were
339 performed on a local spatial scale (**Fig 1b**), although a few studies presented landscape scale

340 experiments. In our sample, local scale studies in general received less attention in the
341 literature compared to studies spanning larger spatial scales when measured in terms of
342 citation rates (**Fig 1b**).

343

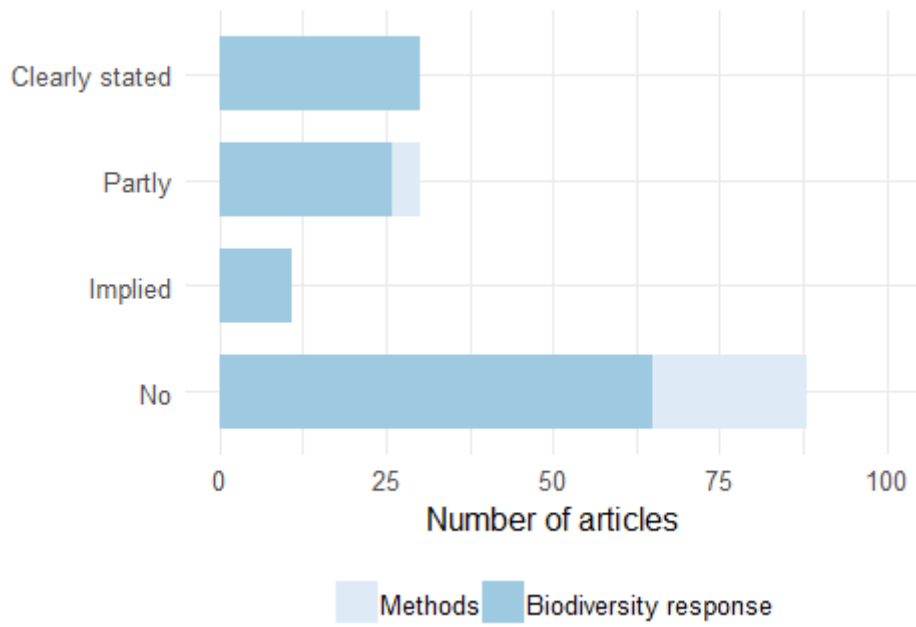
344 Figure Legends

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

351

352 Figures

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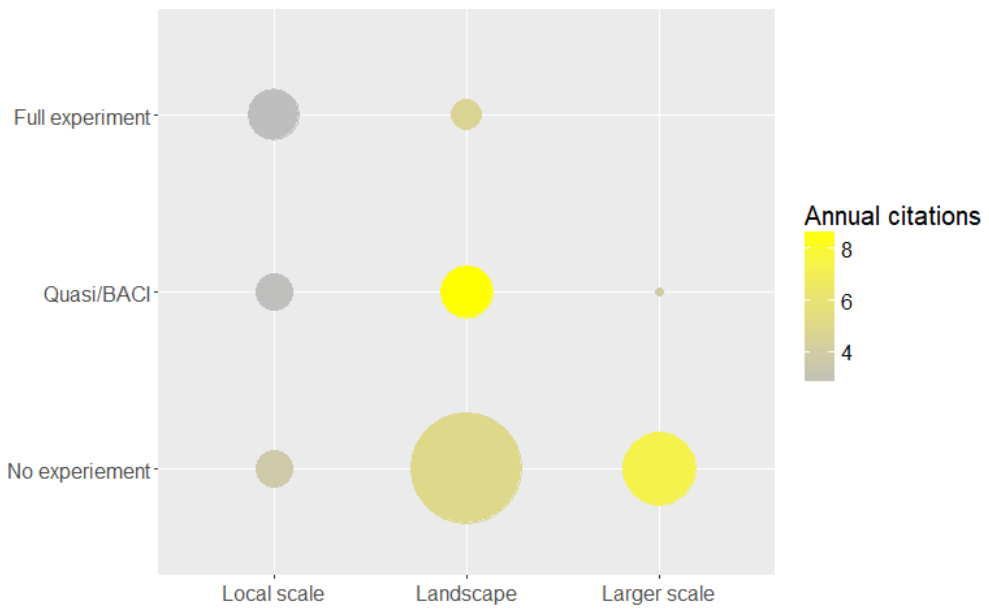
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355 **Fig 1a**

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360 **Fig 1b**