

1 Exploratory and confirmatory research in the open science era

2 *Erlend B. Nilsen¹, Diana E. Bowler¹⁻⁴ & John D.C. Linnell¹*

3 1: Norwegian Institute for Nature Research, P.O. 5685 Torgarden, 7485 Trondheim, Norway

4 2: German Centre for Integrative Biodiversity Research (iDiv), Deutscher Pl. 5E, 04103

5 Leipzig, Germany

6 3. Institute of Biodiversity, Friedrich Schiller University Jena, Dornburger Straße 159, 07743

7 Jena, Germany

8 4. Helmholtz Center for Environmental Research - UFZ, Department of Ecosystem Services,

9 Permoserstraße 15, 04318 Leipzig, Germany

10

11 **Corresponding author:** Erlend B. Nilsen (erlend.nilsen@nina.no)

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15 Abstract:

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

37 structured testing of hypotheses about causal mechanisms from observational
38 biodiversity data.

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

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45 1. Rigorous science in applied ecology

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

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

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

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

75

76 1.1 A mature research community should value both exploration and 77 confirmation

78 One consequence of the “Open Science” movement (Nosek *et al.* 2015) is the focus on open
79 sharing of research data (Wilkinson *et al.* 2016). Increasing accessibility to data allows
80 researchers to apply an ever-widening range of models to data for exploratory science. This
81 contrast with the pleas for more widespread adoption of confirmatory research, where
82 hypotheses are described *a-priori* and then carefully tested based on empirical data
83 collected specifically for that purpose (Caughley 1994; Houlahan *et al.* 2017). We agree with
84 the plea for more formal testing of scientific hypotheses in applied ecological research, but
85 would also like to highlight the fundamental role that descriptive studies documenting the
86 state of local or global biodiversity, or the natural history of species has for conservation
87 science (Beissinger & Peery 2007; Pereira *et al.* 2013). Exploratory research could also
88 generate new hypothesis that could formally be tested later. Moreover, a movement
89 towards more planetary scale assessments, such as those carried out by the
90 Intergovernmental Panel on Biodiversity and Ecosystem Services (IPBES), makes it unfeasible

91 for policy to rely mainly on insights gained from experimental research (Mazor *et al.* 2018;
92 Box 1). Our rapid screening of the literature indeed suggests that large-scale studies often
93 have a large impact, at least if measured through citation rates (**Box 1**).

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

109

110 1.2 Novel ways to test ecological theories

111 Our brief survey of the literature (**Box 1**) (see also Betini, Avgar & Fryxell 2017; Sells *et al.*
112 2018) suggest that most research does not conform to strict hypothesis-testing. However, in
113 the open science era, there are ample possibilities to increase the use and impact of

114 confirmatory research, by more widely embracing new tools, methods, and increased data
115 availability.

116 Strict experiments in applied ecology (**Box 1**) are generally conducted at small spatial scales
117 (although there are some notable exceptions, e.g. Krebs, Boutin & Boonstra 1995; Wiik *et al.*
118 2019). This contrasts the fact that many ecological and policy processes operate at far larger
119 scales (Estes *et al.* 2018). Better utilization of large-scale unreplicated natural experiments
120 could improve understanding of causal relationships in ecological systems (Barley &
121 Meeuwig 2017), especially the impacts of rare and extreme events (e.g. Gaillard *et al.* 2003).
122 Such natural experiments provide researchers with the opportunity for a real-world test of a
123 hypothesis, and can be seen as “conceptual” replications where different systems and
124 approaches are used to test the same theory. A complementary approach is to integrate
125 findings from small-scale manipulative experiments into analysis of large scale observational
126 data (Kotta *et al.* 2019). Such integration will necessitate closer collaboration between
127 ecologists working at different spatial scales, and between experimentalists and modellers
128 (Heuschele *et al.* 2017). The increased availability of hierarchical statistical models that
129 integrate data from disparate sources has high potential to facilitate such an integration
130 (Isaac *et al.* 2019). In the new era of open science, large amounts of data from both field
131 surveys and experiments are now becoming available, widening the range of opportunities
132 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 strengthen a causality
135 inference from observational data (Law *et al.* 2017). Causal inference approaches force
136 researchers to think more deeply about the direct and indirect relationships of variables in

137 their study systems (Ferraro, Sanchirico & Smith 2019). These approaches include controlling
138 for confounding factors by matching (to control observable confounders) and use of panel
139 data and synthetic controls to control for unobservable confounders, as well as instrumental
140 variables to eliminate unobservable confounders (reviewed by Law *et al.* 2017). Time-series
141 observational data are particularly useful because they are unidirectional - cause must
142 precede effect (Dornelas *et al.* 2013) and approaches such as convergent cross mapping are
143 designed to test for causal effects (Sugihara *et al.* 2012)

144 Insights into causality should not be seen as a “one-off” test, and an accumulation of
145 knowledge through replication is fundamental for a robust knowledge base. Triangulation -
146 whereby several approaches are formally applied to the same problem - is therefore useful
147 for assessing the reliability of causal claims (Munafò & Smith 2018). In general, a wider
148 adoption of systematic reviews and other structured evidence synthesis methods would
149 allow more robust assessment of the evidence base (Pullin & Stewart 2006). In the open
150 science era, evidence synthesis can increasingly be based on open data rather than on
151 published effect sizes (Culina *et al.* 2018).

152

153 1.3 Journals, editors, and reviewers should assist in the change

154 Journal editors play an important role in facilitating scientific rigor of the studies that
155 underpin real-life management decisions. This could further strengthened by creating new
156 incentives for more honest and open reporting from the research process. We acknowledge
157 that many of these processes are already starting to happen across the ecosystem of
158 journals.

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

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

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, and
180 fair attribution of credit to those that originally proposed the hypothesis. It would also

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

183 2. Outlook

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

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197 [Acknowledgement](#)

198 We are grateful to many people at our research department for fruitful discussions about
199 this topic over the last years. EBN, DB and JDCL received funding from the Research Council
200 of Norway (grant 251112).

201

202 **Data accessibility:** Data is available at Dryad (<https://doi.org/10.5061/dryad.v9s4mw6r3>); R-
203 scripts and additional files are available at <https://osf.io/n8fum/>.

204

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

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314 Box 1: Hypotheses and experiments in applied ecology

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

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

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

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

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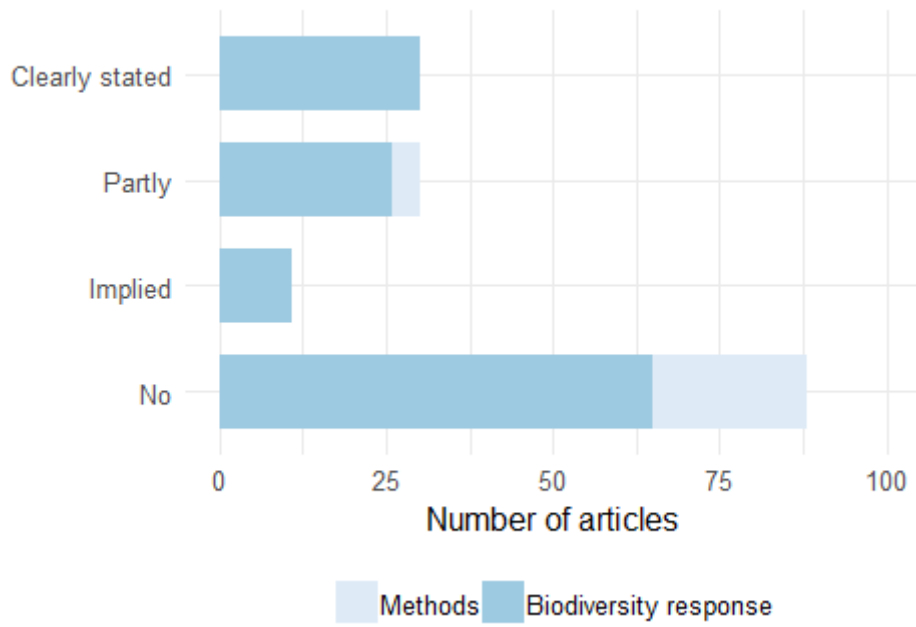
347 Figure Legends

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

354

355 Figures

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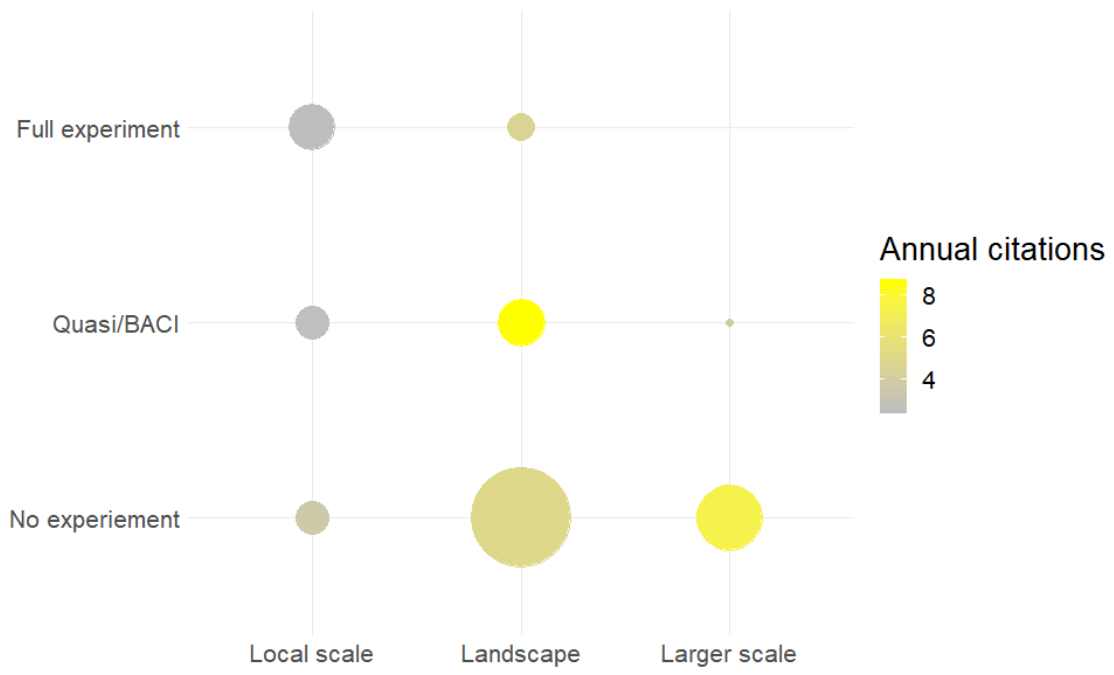
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358 **Fig 1a**

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363 **Fig 1b**