

Code-sharing policies are associated with increased reproducibility potential of ecological findings

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Data and code availability statement

All data and code are available in Zenodo (Sánchez-Tójar et al. 2025).

Abstract

Software code (e.g., analytical code) is increasingly recognized as an important research output because it improves transparency, collaboration, and research credibility. Many scientific journals have introduced code-sharing policies; however, surveys have shown alarmingly low compliance with these policies. In this study, we expanded on a recent survey of ecological journals with code-sharing policies by investigating sharing practices in a comparable set of ecological journals without code-sharing policies. Our aims were to estimate code- and data-sharing rates, assess key reproducibility-boosting features, such as the reporting of software versioning, and compare reproducibility potential between journals with and without a code-sharing policy. We reviewed a random sample of 314 articles published between 2015 and 2019 in 12 ecological journals without a code-sharing policy. Only 15 articles (4.8%) provided analytical code, with the percentage nearly tripling over time (2015-2016:2.5%, 2018-2019:7.0%). Data sharing was higher than code-sharing (2015-2016:31.0%, 2018-2019:43.3%), yet only eight articles (2.5%) shared both code and data. Compared to a comparative sample of 346 articles from 14 ecological journals with a code-sharing policy, journals without a code-sharing policy showed 5.6 times lower code-sharing, 2.1 times lower data-sharing, and 8.1 times lower reproducibility potential. Despite these differences, the key reproducibility-boosting features of the two journal types were similar. Approximately 90% of all articles reported the analytical software used; however, for journals with and without a code-sharing policy, the software version was often missing (49.8% and 36.1% of articles, respectively), and exclusively proprietary (i.e., non-free) software was used in 16.7% and 23.5% of articles, respectively. Our study suggests that journals with a code-sharing policy have greater reproducibility potential than those without. Code-sharing policies are likely to be a necessary but insufficient step towards increasing reproducibility. Journals should prioritize the adoption of explicit, easy-to-find, and strict code-sharing policies to facilitate researcher compliance and implement mechanisms such as checklists to ensure compliance.

Keywords: replicability, reliability, robustness, generalizability, verification, replication, FAIR, checklist

40 Introduction

41 Sharing software code is essential for robust, reproducible, and impactful science (Peng 2011; Borregaard
42 and Hart 2016; Lewis et al. 2018; Cole et al. 2024). Software code is used to process and analyze data,
43 create figures, and even produce fully executable articles (Mislán et al. 2016; Lasser 2020), and code
44 complexity is increasing (Touchon and McCoy 2016; Feng et al. 2020). Code helps with understanding and
45 critically evaluating data analysis and, importantly, can be used and extended by others, allowing faster
46 scientific progress (Cadwallader et al. 2022). The computational reproducibility of scientific findings (i.e.,
47 using the same code on the same data to reproduce the same results; Benureau and Rougier 2018), a
48 seemingly simple but difficult-to-achieve feature in modern science (e.g., Campbell et al. 2023; Kambouris
49 et al. 2024), greatly improves when analytical code is available (Laurinavichyute et al. 2022).

50 Code availability has been slowly increasing in ecology (Maitner et al. 2024; Sperandii et al. 2024) and
51 other fields (Cao et al. 2023; but see Serghiou et al. 2022), which is likely a consequence of several
52 changes. First, software and software codes are being recognised as essential research outputs (DORA:
53 <https://sfdora.org/read/>; ReSA: <https://www.researchsoft.org/>; Jay et al. 2021). Second, training and
54 guidelines on reproducible codes and software management are more available to researchers (Donoho
55 et al. 2008; McKiernan 2017; Kohrs et al. 2023). Third, funders and journals have slowly but steadily
56 introduced code-sharing policies. For example, the percentage of journals with a code-sharing policy
57 increased rapidly for a subset of 96 ecological journals, from 15% in 2015 (Mislán et al., 2016) to 75% in
58 2020 (Culina et al. 2020). A larger survey of 275 journals in ecology and evolution found that 72%
59 mandated or encouraged code-sharing as of 2024 (Ivimey-Cook et al. 2025). However, there is
60 accumulating evidence that the mere existence of journal code-sharing policies likely increases code
61 availability (Cadwallader et al. 2022; Fišar et al. 2024; Ivimey-Cook et al. 2025), even when policy
62 compliance is alarmingly low. For example, only 27% of articles published between 2015 and 2019 in a
63 subset of 96 ecological journals with a code-sharing policy shared their code (Culina et al. 2020), showing
64 that policies are only partially efficient if they are not enforced. In addition, policies that do not specify
65 and require best-sharing practices likely lead to low code reusability and, ultimately, low reproducibility
66 of scientific findings.

67 Code-sharing does not necessarily translate into code that is easy to understand, adapt, and reuse.
68 Multiple technical challenges to code reuse range from dependencies on the original researcher's
69 computational environment, such as the operating system and libraries used, to inadequate
70 documentation on how to install, run, and use the code (Boettiger 2015). Code can also easily *rot* after
71 software updates, leading to changes in functionality, compatibility, and, ultimately, the reproducibility
72 of the results (Hinsen 2019). Although container technology such as Docker, which packages software and
73 its dependencies into a standardized environment, has been suggested as a solution to improve portability
74 and reproducibility (Boettiger 2015; Grüning et al. 2018; Essawy et al. 2020; Trisovic et al. 2022), its
75 adoption remains low (e.g., Venkatesh et al. 2022). At the minimum, the software and packages that are
76 fundamental for the analyses should be stated and appropriately referenced in the main manuscript, and
77 the version(s) used should be clearly stated (guidelines for software citation: Chue Hong et al. 2019). The
78 remaining packages should be documented as part of stand-alone documentation (e.g., README, or inline
79 comments; Benureau and Rougier 2018; Jenkins et al. 2023; Ivimey-Cook et al. 2023). Software and
80 package citation is important for computational reproducibility but also to better explain the methodology
81 and give credit to software developers. In addition, the code should ideally be written using free (i.e., non-
82 proprietary) and open-source software (also known as FOSS; Ostermann and Granell 2016) such as the
83 free and open-source R programming language (R Core Team 2023) which is widely used in ecology (Lai
84 et al. 2019; Culina et al. 2020; Kambouris et al. 2024). Furthermore, code should be shared in a permanent
85 repository (e.g., Zenodo) and assigned an open and permissive licence and a persistent identifier such as

86 a DOI (Krafczyk et al. 2021; Kim et al. 2022; Jenkins et al. 2023). This is particularly important given the
87 far-from-ideal rates of link persistence found for scientific code in fields such as astrophysics (Allen et al.
88 2018; Sperandii et al. 2024).

89 Our main goal was to examine whether the implementation of code-sharing policies by journals leads to
90 higher rates of code-sharing and overall reproducibility potential. For that, we assessed the code-sharing
91 and reporting features of 314 articles published in 12 ecological journals without a code-sharing policy,
92 and compared them with those from the comparable sample of 346 articles published in 14 ecological
93 journals with a code-sharing policy from Culina et al. (2020). We predict that ecological journals without
94 a code-sharing policy will have lower rates of sharing than journals with a code-sharing policy. However,
95 we do not have a clear expectation of whether the reporting of features associated with higher long-term
96 reproducibility, such as the software used, its versioning and accessibility (free or not), and the location
97 where code is shared, will differ between both sets of journals. This is because often code-sharing policies
98 are not explicit (Ivimey-Cook et al. 2025), and thus they might not explicitly prompt authors to follow best
99 practices, whereas authors who share their code in the absence of code-sharing policies might be primed
100 to follow best practices. Finally, we anticipate that code availability and the reporting of features
101 associated with higher long-term reproducibility will increase over time, regardless of the existence of
102 code-sharing policies, given recent changes in scientific attitudes and norms and the rise of open science
103 (Cao et al. 2023).

104 **Methods**

105 Our study design closely matches that of Culina et al. (2020), who surveyed 14 ecological journals with a
106 code-sharing policy from 2015 to 2019. Thus, readers are referred to Culina et al. (2020) for further
107 information on methodology, and importantly, results for journals with a code-sharing policy. In the
108 follow-up study here, we aimed to identify 14 comparable ecological journals without a code-sharing
109 policy for the same period (i.e., 2015-2019). For this, we used a set of 96 ecological journals originally
110 assessed by Mislán et al. (2016) and subsequently reassessed by Culina et al. (2020) and identified 12
111 journals without a code-sharing policy as of 2020. This was accomplished by carefully reading the author
112 guidelines and open research policies of these journals compiled by Culina et al. (2020). While initially, we
113 identified 24 potentially eligible journals (i.e., without a code-sharing policy), we later removed from the
114 list two review journals ('Trends in Ecology and Evolution', and 'Annual Review of Ecology, Evolution, and
115 Systematics'), nine journals that mentioned code as part of their data-sharing policy ('Aquatic Microbial
116 Ecology', 'Behavioral Ecology and Sociobiology', 'Ecology and Evolution', 'Global Change Biology', 'Journal
117 of Soil and Water Conservation', 'Marine Ecology Progress Series', 'Microbial Ecology', 'Oryx', and
118 'Paleobiology'), and one journal that had been discontinued ('Journal of the North American Benthological
119 Society'). We judged the remaining 12 journals eligible (i.e., no code-sharing policy by March 2020; see
120 Table S1 in Culina et al. 2020), as they did not mention programming code or other terms that could be
121 interpreted as such (e.g., script, research artefacts) in their author guidelines: 'Basic and Applied Ecology',
122 'Behavioral Ecology', 'Ecosystems', 'Freshwater Science', 'Frontiers in Ecology and the Environment',
123 'International Journal of Sustainable Development and World Ecology', 'Journal of Plant Ecology',
124 'Landscape Ecology', 'Oecologia', 'Oikos', 'Polar Research', and 'Wildlife Research'. Note that since the
125 initial screening in March 2020, some of these journals might have adopted a code-sharing policy;
126 however, this would not affect our study as here we focused on articles published between 2015 and
127 2019. In addition, readers should be aware that our study was design to allow us to fully compare in detail
128 our results for journals without a code-sharing policy to those with from Culina et al. (2020), so we
129 restricted our searches from 2015 to 2019. Subsequently, the general figures on data- or code-sharing
130 and reporting practices reported here might not be representative of current ones, for which we refer to
131 recent surveys (Maitner et al. 2024; Sperandii et al. 2024).

132 We performed a search in the Web of Science Core Collection (databases covered: Science Citation Index
133 Expanded (SCI-EXPANDED) since 1945, Social Sciences Citation Index (SSCI) since 1956, Arts & Humanities
134 Citation Index (AHCI) since 1975, Emerging Sources Citation Index (ESCI) since 2017) in February 2022, and
135 extracted all the records published in the 12 journals during the same two distinct temporal periods as
136 Culina et al. (2020): (i) from the 1st of June 2015 to the 9th of December 2016 (N = 2499 records); and (ii)
137 from the 1st of January 2018 to the 21st of May 2019 (N = 2275 records). We then took a random sample
138 of 200 articles from each of these two periods (N = 400 in total) using the function ‘sample()’ in R v.4.3.1
139 (R Core Team, 2023). We screened their titles and abstracts for eligibility using Rayyan software (Ouzzani
140 et al. 2016). To meet our inclusion criteria, an article had to conduct a statistical analysis, develop and run
141 a mathematical model, or conduct simulations. Following Culina et al. (2020), we excluded reviews,
142 opinions, commentaries, and purely bioinformatics studies. In addition, we excluded two articles from the
143 2018-2019 subset that performed landscape analyses because we lacked expertise to understand the
144 analyses and software used. Each article was screened by two reviewers (AB, AST), and conflicts among
145 them (~5%) were resolved collectively. In total, 314 non-molecular articles passed the title-and-abstract
146 screening, and their full-text was read in detail for data extraction. The screening process is presented in
147 a PRISMA diagram (Figure S1; O’Dea et al. 2021).

148 Data extraction for each article was conducted by two reviewers (AB and either AST, AC, or MP) to increase
149 the reproducibility and reliability of the data extraction process. Any conflicts were resolved by involving
150 a third reviewer and are marked and explained in the provided data (see ‘data and code availability
151 statement’). For each article, we recorded (i) bibliographic information (title, authors, journal, publication
152 year), (ii) the type of analyses conducted since our interest was only on articles performing statistical
153 analyses and/or simulations, (iii) whether code and data (if used) had been shared (levels: yes, no,
154 partially), (iv) for instances of shared code, we recorded where it was shared (levels: repository,
155 supplementary material, website), and the name of the repository (if used), and (iv) several additional key
156 reproducibility-boosting features (i.e., software and additional package(s)/extension(s) (hereafter
157 referred to as “package(s)”) used, number of software and package(s) for which version was provided,
158 and whether the software used was free (i.e., non-proprietary; levels: yes, no, partially; where partially
159 refers to having used both free and non-free software). Figures were generated using the R package
160 ‘ggplot2’ v.3.5.1 (Wickham 2016).

161 To test whether the reproducibility potential is higher in journals with versus without a code-sharing
162 policy, we revisited, updated, and extended the dataset used for the analyses presented by Culina et al.
163 (2020). Specifically, for the 346 nonmolecular articles included in Culina et al. (2020), we extracted the
164 package(s) used and the number of software and package(s) for which version was provided. We also
165 checked the already collected variables of interest from Culina et al. (2020) for inconsistencies.

166 Post-hoc decisions we made when processing our data were: (1) whenever packages or extensions were
167 not reported, we assigned the number of packages as 0, even if the software used may not actually have
168 any packages or extensions. We did this because it was not possible for us to find out information about
169 the existence of packages or extensions for all the software reported; (2) for articles that shared some or
170 all of their data only within figures (e.g., in a scatterplot), we assigned them as not sharing their data; (3)
171 we searched for software and package versions within the main article and supplementary text (whenever
172 available), including in their reference lists; (4) in some rare cases when the article did not report the
173 software used but we could infer it from the packages or extensions reported, we assigned the software
174 as “Not Stated”.

175

176

177 **Results**

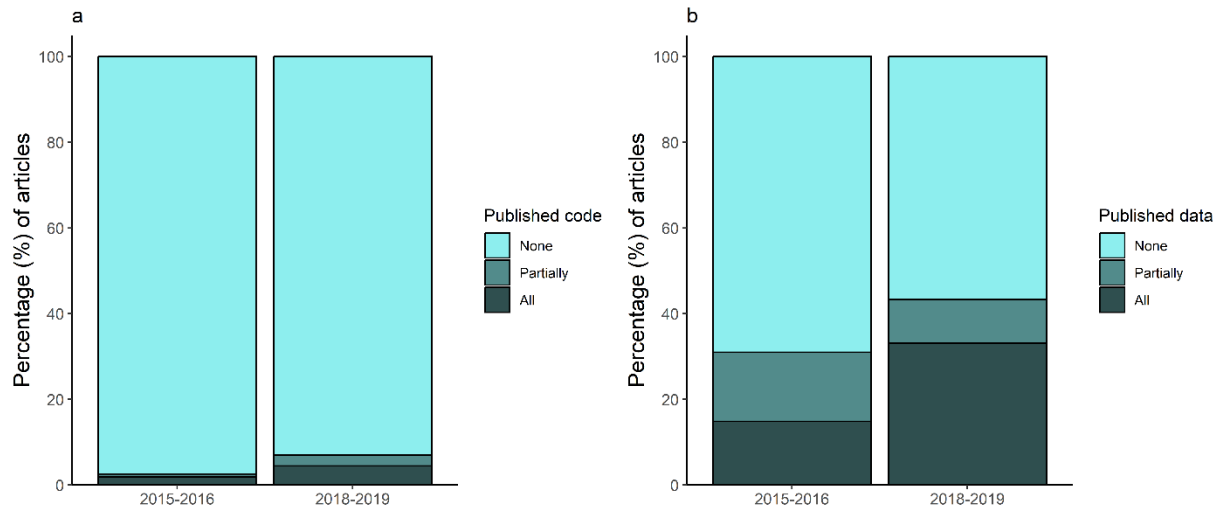
178 Code- and data-sharing

179 We investigated 314 nonmolecular articles that performed statistical analyses or simulations and were
 180 published between 2015 and 2019 (2015-2016:157 articles, 2018-2019:157 articles) in 12 ecological
 181 journals without a code-sharing policy as of March 2020. In these 12 journals, the statistical analysis or
 182 simulation code underlying the research findings was shared in only 15 of 314 articles (4.8%). These 15
 183 articles were accompanied by either seemingly all (10 articles, 3.2%) or some (five articles, 1.6%) of the
 184 code. The overall percentage of code shared increased by approximately threefold over the two periods
 185 (2.5% versus 7.0% in 2015–2016 and 2018–2019, respectively; Figure 1a). At the journal level, the
 186 percentage of articles where code was shared ranged between 0% and 8.7% (median = 1.2%, mean =
 187 3.1%; Table 1), indicating that not sharing code is a general phenomenon across ecological journals
 188 without a code-sharing policy. Of the 15 articles that shared code, 12 (80%) provided it as part of the
 189 article’s supplementary material, one (6.7%) at a website, and only two (13.3%) in a repository (i.e.,
 190 Dryad).

191 **Table 1.** Code- and data-sharing for 314 nonmolecular articles that conducted statistical analysis or
 192 simulations [i.e., did not use data] published between 2015 and 2019 in 12 ecological journals without a
 193 code-sharing policy.

Journal	Total number of articles sampled [using data]	Number of articles providing code (%)	Number of articles providing data (%)
<i>Basic and Applied Ecology</i>	12 [12]	0 (0.0%)	2 (16.7%)
<i>Behavioral Ecology</i>	44 [44]	3 (6.8%)	25 (56.8%)
<i>Ecosystems</i>	23 [23]	2 (8.7%)	10 (43.5%)
<i>Freshwater Science</i>	16 [16]	0 (0.0%)	1 (6.2%)
<i>Frontiers in Ecology and the Environment</i>	4 [4]	0 (0.0%)	2 (50.0%)
<i>International Journal of Sustainable Development and World Ecology</i>	6 [6]	0 (0.0%)	1 (16.7%)
<i>Journal of Plant Ecology</i>	20 [20]	0 (0.0%)	4 (20.0%)
<i>Landscape Ecology</i>	44 [44]	1 (2.3%)	21 (47.7%)
<i>Oecologia</i>	79 [79]	5 (6.3%)	19 (24.1%)
<i>Oikos</i>	42 [40]	3 (7.1%)	25 (62.5%)
<i>Polar Research</i>	7 [7]	0 (0.0%)	4 (57.1%)
<i>Wildlife Research</i>	17 [17]	1 (5.9%)	2 (11.8%)

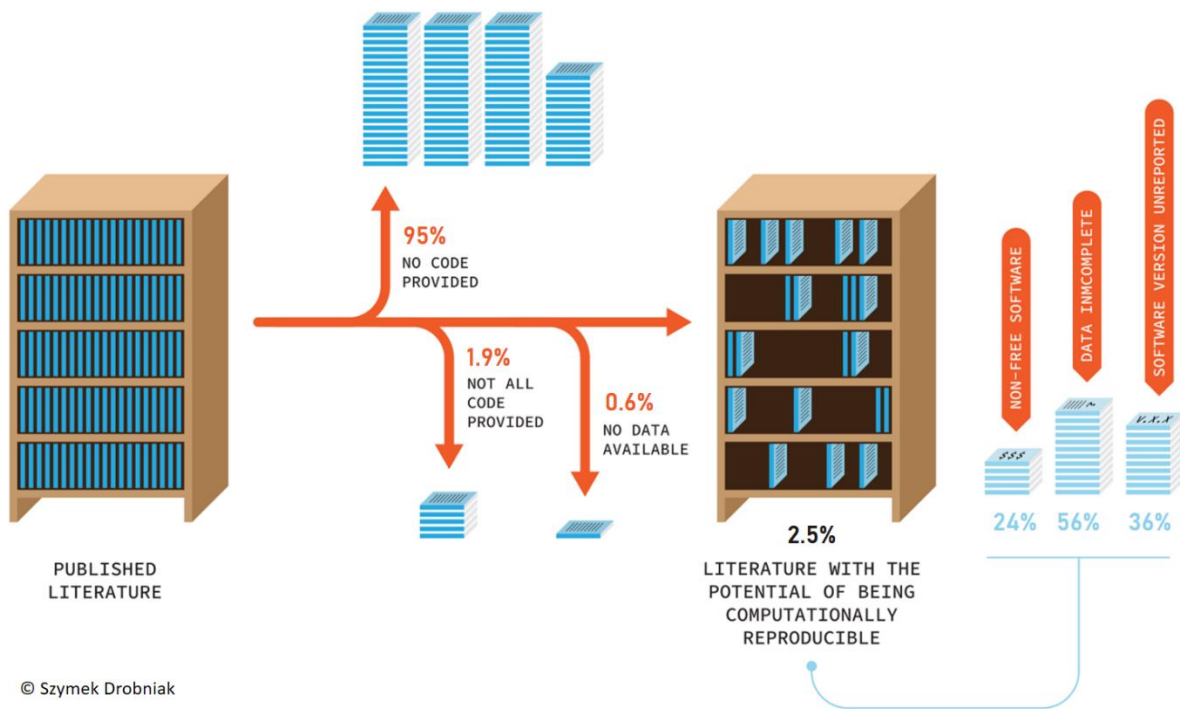
194
 195 In the 12 journals without a code-sharing policy, data were shared in 116 of the 312 nonmolecular articles
 196 that used data (37.2%). These articles were accompanied by either seemingly all (75 articles, 24.0%) or
 197 some (41 articles, 13.1%) of the data, and the overall percentage of shared data increased by
 198 approximately 40% over the 5-year period studied (31.0% vs. 43.3%, in 2015–2016 and 2018–2019,
 199 respectively; Figure 1b). Furthermore, at the journal level, the percentage of articles in which data were
 200 shared ranged between 6.2% and 62.5% (median = 33.8%, mean = 34.4%; Table 1), suggesting large
 201 differences in data-sharing across the 12 ecological journals without a code-sharing policy.



202

203 **Figure 1.** Code- and data-sharing are uncommon in 12 ecological journals without a code-sharing policy. Percentage
 204 of nonmolecular articles surveyed that provided code (a) or data (b) for each of the periods studied (2015–2016: 157
 205 articles, 2018–2019: 157 articles).

206 Altogether, only 8 (2.5%) articles had seemingly shared both all data (if any used) and all code, meaning
 207 that the potential for computational reproducibility in the 12 ecological journals without a code-sharing
 208 policy surveyed in our study could be as low, and likely lower than 2.5% (Figure 2). This percentage is 8.2
 209 times smaller than the corresponding percentage found in journals with a code-sharing policy (20.8%;
 210 Culina et al. 2020).



211

212 **Figure 2.** Diagram visually representing the computational reproducibility potential of articles published between
 213 2015 and 2019 in ecological journals without a code-sharing policy. The value corresponding to “Data incomplete”

214 used in the diagram (56%) was obtained from Roche et al. (2015); whereas all the remaining values correspond to
215 the survey presented in the current study. Original illustration by Szymek Drobnik.

216 Features boosting long-term reproducibility in journals with and without a code-sharing policy

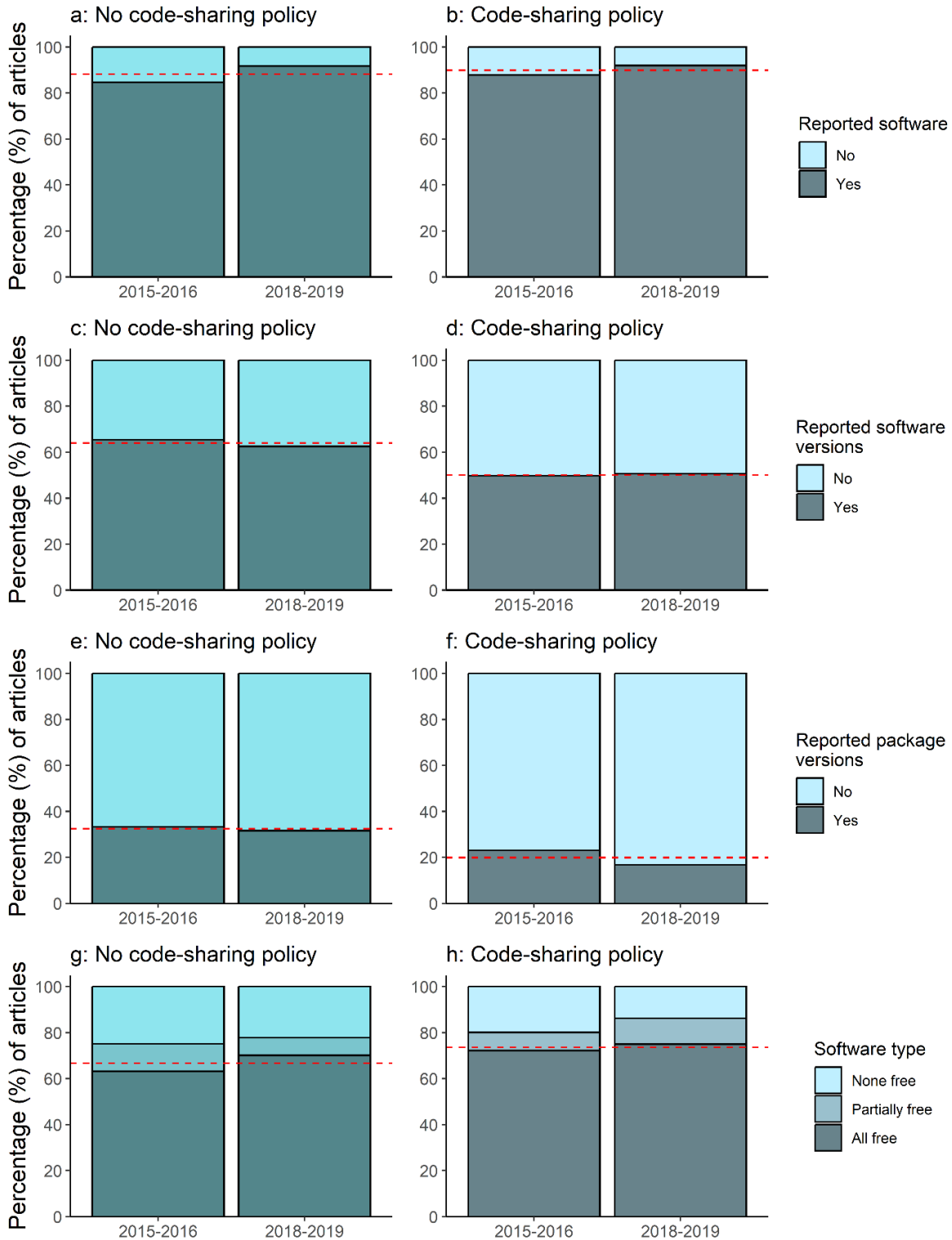
217 Our survey showed that 88.2% of articles (N = 277) published in journals without a code-sharing policy
218 stated the analytical software used (Figure 3a), a value that is almost identical to the 89.9% (N = 311)
219 found for articles published in journals with a code-sharing policy (Culina et al. 2020; Figure 3b). For those
220 stating the statistical software used, 63.9% (N = 177) of the articles published in journals without a code-
221 sharing policy reported the version of all software used (Figure 3c), whereas that percentage was 50.2%
222 (N = 156) for articles published in journals with a code-sharing policy (Figure 3d). The mean number of
223 analytical software used was 1.27 (median = 1.00, range = 1–6) in journals without a code-sharing policy
224 and 1.81 (median = 1.00, range = 1–14) in journals with a code-sharing policy. The reporting of software
225 versioning remained slightly higher for journals without a code-sharing policy than for those with when
226 expressed as the average percentage of software with version per article (without policy: median = 100%,
227 mean = 67.5%, range: 0–100%; with policy: median = 100%, mean = 59.6%, range: 0–100%).

228 For articles stating that they used additional packages, 32.4% (N = 46) of the articles published in journals
229 without a code-sharing policy provided the version of all packages used (Figure 3e), whereas that
230 percentage was 19.5% (N = 40) for articles published in journals with a code-sharing policy (Figure 3f). The
231 mean number of packages reported was 2.30 (median = 2.00, range = 1 to 10) in journals without a code-
232 sharing policy and 2.41 (median = 2.00, range = 1 to 14) in journals with a code-sharing policy. The
233 reporting of package versioning remained slightly higher for journals without a code-sharing policy than
234 for those with when expressed as the average percentage of software with version per article (without
235 policy: median = 33.3%, mean = 45.1%, range: 0–100%; with policy: median = 0%, mean = 30.8%, range:
236 0–100%).

237 For articles stating the statistical software used, 23.5% (N = 65) of articles published in journals without a
238 code-sharing policy used exclusively non-free (i.e., proprietary) software (Figure 3g), compared to 16.7%
239 (N = 52) of articles published in journals with a code-sharing policy (Figure 3h).

240 **Discussion**

241 Our results show that code-sharing is almost non-existent (5%) for non-molecular articles published in
242 ecological journals without a code-sharing policy, a figure that is about six times lower than a comparative
243 sample from journals with a code-sharing policy. Data availability fared better, with about one-third of
244 the articles published in ecological journals without a code-sharing policy sharing data, which corresponds
245 to about half the rate observed in journals with a code-sharing policy. These low sharing rates lead to an
246 extremely low reproducibility potential (less than 3%) of the results published in journals without a code-
247 sharing policy. Importantly, this is likely an overestimation because we also found that key reproducibility
248 features (e.g., software name or versioning) were mostly lacking. Overall, our results confirm previous
249 surveys in ecology and other fields: code-sharing is low, and simply implementing a code-sharing policy
250 likely increases code-sharing but not to the desired level. Below, we place our results within and across
251 fields and discuss code-sharing and the importance of explicit policies. We also provide suggestions for
252 journals on how to improve code-sharing and the (long-term) reproducibility of scientific findings (Box 1).



253

254 **Figure 3.** Features boosting long-term reproducibility in journals with (b, d, f, h; right-hand side panels) and without
 255 a code-sharing policy (a, c, e, g; left-hand side panels). The red dashed line corresponds to the mean for the category
 256 coloured in black (i.e., No software reported, Software versions reported, Package versions reported, and Free
 257 software, respectively). “Partially free” in panels g and h refers to articles that used both free and non-free software.

258 Open science practices are on the rise. When asked, most scientists agreed with the general open science
259 norms and values decades ago (Anderson et al. 2007), but only recently have we started to see more
260 evidence of scientists not only agreeing but also adhering to such norms and values. For example, a recent
261 survey in social sciences found that the percentage of scientists who self-reported using open science
262 practices increased from 49% in 2010 to 87% in 2020 (Ferguson et al. 2023; see also Borycz et al. 2023).
263 Meta-research studies have confirmed that several transparency indicators, including, but not limited to,
264 data- and code-sharing, are on the rise in ecology (Evans 2016; Culina et al. 2020; Roche et al. 2022a) and
265 other fields (Heumüller et al. 2020; Cao et al. 2023; Colavizza et al. 2024; Sharma et al. 2024). Our current
266 survey detected similar trends in ecological journals without a code-sharing policy, with code-sharing
267 tripling from 2015-2016 (2.5%) to 2018-2019 (7.0%). Our results also support the observations from
268 previous meta-research studies on authors being more likely to share data than code in ecology (Culina
269 et al. 2020) and other fields (Bellomo et al. 2024; Sharma et al. 2024). Researchers may perceive greater
270 risks and fewer benefits associated with sharing code compared to data, including unfamiliarity with best
271 sharing practices, insecurity about code quality, fear of misuse or unsolicited appropriation of ideas, and
272 excess preparation costs (Cadwallader & Hrynaskiewicz, 2022; Gomes et al., 2022), coupled with a lack
273 of incentives for code-sharing. This discrepancy might also be in part due to journal policies often having
274 a stronger emphasis on data- than code-sharing (Page et al. 2022; Ivimey-Cook et al. 2025) and is likely
275 less evident in sub-disciplines that rely heavily on computational methods, such as computational biology
276 and software engineering (Heumüller et al. 2020; Cadwallader et al. 2022).

277

BOX 1. How can journals increase code availability? Here is a list of suggestions for journals sorted by the ease of implementation. For more information, journals should consider contacting the journal liaison officer of the Society for Open, Reliable and Transparent Ecology and Evolutionary Biology (SORTEE; <https://www.sortee.org/>).

- Introduce a code-sharing policy: this can range from simply mandating a code availability statement (Hamilton et al. 2023; Sharma et al. 2024) to encouraging or, in the best case, mandating code-sharing, ideally coupled with policy enforcement (Ivimey-Cook et al. 2025). Policies should be clearly written, explicit and easy to find, and ideally shared among journals within and/or among publishers (Christian et al. 2020).
- Implement a reproducibility checklist: this should integrate a minimal list of code-sharing best practices such as the use of persistent identifiers like DOIs which ensure long-term accessibility and proper attribution (Gewin 2016; Trisovic et al. 2022) or ensuring all software and their versioning is provided. Journals should also offer clear guidelines (and support) for authors on how to share code, report software and adhere to reproducibility standards.
- Review and verify code: ask authors to share their code upon first submission to allow reviewers to have access and review the code. Encourage reviewers to use code (and data) during their reviews (Ivimey-Cook et al. 2025). Consider officially integrating code review as part of the editorial process by adding data and code editors to ensure code functionality and adherence to standards (Krafczyk et al 2021).

278 Importantly, our results suggest that journals likely have a central role in increasing code-sharing rates:
279 code-sharing was higher among nonmolecular articles published in journals with a code-sharing policy
280 (27%) than those published in journals without a code-sharing policy (4.8%). A recent survey of meta-
281 analyses in ecology and evolutionary biology detected similar patterns (21.2% and 9.1%, respectively,
282 Kambouris et al. 2024). Previous studies also suggested a link between the introduction of code-sharing
283 policies and a subsequent increase in code availability. For example, code-sharing has increased from 53%
284 in 2019 and 61% in 2020 to 87% in 2022 after the introduction of a mandatory code-sharing policy by PLOS
285 Computational Biology (Cadwallader et al. 2022). Similarly, the percentage of initial submissions providing
286 a link to data and/or code increased from 16.9% in 2021 to 42.6% in 2023 after Ecology Letters changed
287 their sharing policy from simply providing a statement to mandating (and enforcing) providing a link to
288 data and code (Ivimey-Cook et al. 2025; for other examples, in ecology and beyond see Evans 2016;
289 Hamilton et al. 2023; Ellis et al. 2024; Bellomo et al. 2024; Sperandii et al. 2024). Regardless of whether
290 journals have a code-sharing policy, we also detected trends of an increase in code availability over time.
291 This is likely caused by other factors such as changes in norms, better training, and better support in code-
292 writing and sharing.

293 While having a policy helps to increase code-sharing, it is certainly not enough without enforcing
294 compliance (Culina et al. 2020). Our previous survey of 14 ecological journals with a code-sharing policy
295 study indicated that the strictness of the policy did not affect code availability because the percentage of
296 articles sharing code was similar between journals with encouraged (mean and range: 29.7% [14-50%],
297 three journals), mandatory (23.0% [22-38%], five journals), and encouraged/mandatory (24.3% [7-53%],
298 six journals) policies (Culina et al. 2020). A recent survey in biomedical research found more promising
299 rates, with up to 50% of articles published in eight journals with a code-sharing policy making code
300 availability and the likelihood of code-sharing being double in journals with mandatory policies compared
301 to encouraged policies (Sharma et al. 2024). Overall, despite low compliance, which has been linked to
302 factors such as difficult-to-find or unclear written sharing policies (Christian et al. 2020), these examples
303 suggest that even under low policy enforcement, policy interventions can shift research practices towards
304 greater openness. Indeed, implementing a code-sharing policy is a positive step forward, even when
305 resources for enforcing such a policy and reviewing code (e.g., by adopting data and code editors) are not
306 yet available.

307 We found that features boosting long-term reproducibility, such as using free software and reporting its
308 version, were similar between journals with and without a code-sharing policy, suggesting that, although
309 code-sharing policies seem to increase code availability, they might not increase software reporting
310 without being more explicit about best practices. We found that versions of the statistical software and
311 packages were often missing, and approximately a tenth of the articles did not even state the software
312 used. Reporting software and package versions is important for several reasons. First, they can help to
313 understand and solve technical issues related to software dependencies, which are among the most
314 frequently encountered factors hindering computational reproducibility (Laurinavichyute et al. 2022;
315 Kellner et al. 2024; Samuel and Mietchen 2024). Different versions of software and/or packages can lead
316 to inconsistencies in results and even to code rot, which occurs when the code relies on specific versions
317 of software or packages that are no longer available or have undergone significant changes (e.g.,
318 deprecated functions), rendering the code incompatible with current operating systems (Boettiger 2015;
319 Laurinavichyute et al. 2022). Second, software reporting standards are key for computational
320 reproducibility (i.e., obtaining the same results using the same input data and code) but also for analytical
321 reproducibility (i.e., obtaining the same results writing *fresh code* using the provided written
322 methodological descriptions when data but not code are available; Kambouris et al. 2024), and thus
323 should be prioritized by authors and journals alike (Box 1). Finally, about one-fifth of the articles
324 exclusively used non-free (i.e., proprietary) software. Reproducibility is hindered when the code relies on

325 proprietary software that requires license or subscriptions. Proprietary software restricts access to its
326 source code and is inaccessible to researchers who cannot afford it, ultimately limiting independent
327 verification and building upon original research (Ostermann and Granell 2016; Benureau and Rougier
328 2018; Konkol et al. 2019; Laurinavichyute et al. 2022). Ideally, the code used for a study should be peer
329 reviewed to ensure its completeness, reusability, and reproducibility prior to manuscript acceptance
330 (Ivimey-Cook et al. 2023). Before code review becomes a norm, authors, reviewers, and editors should
331 ensure that the minimum requirements for reproducibility are met, which can be facilitated by the use of
332 checklists and policies explicitly linked to best practices. In addition, we advocate for proper software and
333 package citation to give credit to software developers and incentivise software and package development
334 (e.g., using the R package ‘grateful’; Rodriguez-Sanchez and Jackson 2024).

335 Our study has several limitations. Although we matched journals in time and from a seemingly
336 representative list of ecological journals, journals with a code-sharing policy were more likely to have a
337 data-sharing policy too (Ivimey-Cook et al. 2025), which may increase code-sharing simply by increasing
338 the visibility of sharing in general. However, it is fair to assume that some of the 12 journals without a
339 code-sharing policy studied here did not have a data-sharing policy between 2015 and 2019, which may
340 partially account for the lower code-sharing as a by-product. In addition, journals with and without a code-
341 sharing policy may have differed in other transparency indicators or predictors of computational
342 reproducibility, such as the existence of reporting checklists, differences in prestige, or the type of
343 research published. Despite these potential limitations, our study adds to the mounting evidence that
344 journal policies are an important stepping stone to increasing code availability. Finally, a potentially
345 important factor for increasing data and code sharing that was not explored in our study is the funding
346 source, with evidence suggesting that research funded by competitive grants tends to have higher code-
347 and data-sharing rates, presumably because these funding bodies often have mandates or strong
348 recommendations for sharing as part of their grant conditions (Tan et al. 2024). Thus, we not only call on
349 journals to introduce code-sharing policies but also on funders to make a stronger push for mandating
350 data- and code-sharing, regardless of whether they currently have the mechanisms necessary to enforce
351 those policies.

352

353 **Conclusions**

354 In sum, our study adds to the mounting evidence that code-sharing policies increase code availability,
355 which ultimately increases the reproducibility potential of scientific findings. Specifically, our study
356 suggests that based on code and data availability, the computational reproducibility potential is about
357 eight times lower in ecological journals without a code-sharing policy (2.5%) compared to those with one
358 (21%). Importantly, however, these should be considered ceiling values because we also found that
359 software reporting needs improvement to allow reproducibility, and previous studies have found that
360 open code (Obels et al. 2020; Laurinavichyute et al. 2022; Henderson et al. 2024) and data are often
361 incomplete and difficult to use due to poor documentation (Roche et al. 2015; Roche et al. 2022b). The
362 perceived costs and benefits of sharing code and data have been studied, dissected, and discussed in
363 detail elsewhere (Soeharjono and Roche 2021; Gomes et al. 2022; Borycz et al. 2023; Nguyen et al. 2023).
364 Low sharing and reporting are key factors that increase research waste in ecology (Purgar et al. 2022) and
365 other fields (Chalmers and Glasziou 2009), and as such, more efforts are needed to reduce research waste
366 (see more suggestions in Grainger et al. 2020; Buxton et al. 2021; Purgar et al. 2024). Here, we call on all
367 journals and funders to introduce data- and code-sharing policies, even if they currently do not have the
368 resources or mechanisms necessary to enforce them.

369 **Authors contributions**

370 **Alfredo Sánchez-Tójar**: conceptualisation (equal); data curation (lead); formal analysis (lead);
371 investigation (equal); methodology (lead); project administration (equal); software (lead); supervision
372 (equal); visualization (equal); writing – original draft (lead); writing – review and editing (equal). **Aya**
373 **Bezine**: data curation (equal); investigation (equal); writing – review and editing (equal). **Marija Purgar**:
374 data curation (equal); investigation (equal); validation (equal); writing – review and editing (equal). **Antica**
375 **Culina**: conceptualisation (equal); data curation (equal); investigation (equal); project administration
376 (equal); supervision (equal); visualization (equal); validation (equal); writing – original draft (equal);
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378

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391

392 **Competing interest**

393 Alfredo Sánchez-Tójar, Marija Purgar, and Antica Culina are officers of the Society for Open, Reliable, and
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395

396 **References**

397 Allen, A., Teuben, P. J., & Ryan, P. W. (2018). Schroedinger’s Code: A Preliminary Study on Research Source Code Availability
398 and Link Persistence in Astrophysics. *The Astrophysical Journal Supplement Series*, 236(1), 10.

399 <https://doi.org/10.3847/1538-4365/aab764>

400 Anderson, M. S., Martinson, B. C., & De Vries, R. (2007). Normative Dissonance in Science: Results from a National Survey of
401 U.S. Scientists. *Journal of Empirical Research on Human Research Ethics*, 2(4), 3–14.

402 <https://doi.org/10.1525/jer.2007.2.4.3>

403 Bellomo, R. K., Zavalis, E. A., & Ioannidis, J. P. A. (2024). Assessment of transparency indicators in space medicine. *PLOS ONE*,
404 19(4), e0300701. <https://doi.org/10.1371/journal.pone.0300701>

405 Benureau, F. C. Y., & Rougier, N. P. (2018). Re-run, Repeat, Reproduce, Reuse, Replicate: Transforming Code into Scientific
406 Contributions. *Frontiers in Neuroinformatics*, 11, 69. <https://doi.org/10.3389/fninf.2017.00069>

407 Boettiger, C. (2015). An introduction to Docker for reproducible research. *SIGOPS Oper. Syst. Rev.*, 49(1), 71–79.

408 <https://doi.org/10.1145/2723872.2723882>

409 Borregaard, M. K., & Hart, E. M. (2016). Towards a more reproducible ecology. *Ecography*, 39(4), 349–353.

410 <https://doi.org/10.1111/ecog.02493>

- 411 Borycz, J., Olendorf, R., Specht, A., Grant, B., Crowston, K., Tenopir, C., Allard, S., Rice, N. M., Hu, R., & Sandusky, R. J. (2023).
 412 Perceived benefits of open data are improving but scientists still lack resources, skills, and rewards. *Humanities and*
 413 *Social Sciences Communications*, 10(1), 339. <https://doi.org/10.1057/s41599-023-01831-7>
- 414 Buxton, R. T., Nyboer, E. A., Pigeon, K. E., Raby, G. D., Rytwinski, T., Gallagher, A. J., Schuster, R., Lin, H.-Y., Fahrig, L., Bennett, J.
 415 R., Cooke, S. J., & Roche, D. G. (2021). Avoiding wasted research resources in conservation science. *Conservation Science*
 416 *and Practice*, 3(2), e329. <https://doi.org/10.1111/csp2.329>
- 417 Cadwallader, L., & Hrynaszkiewicz, I. (2022). A survey of researchers' code sharing and code reuse practices, and assessment of
 418 interactive notebook prototypes. *PeerJ*, 10, e13933. <https://doi.org/10.7717/peerj.13933>
- 419 Cadwallader, L., Mac Gabhann, F., Papin, J., & Pitzer, V. E. (2022). Advancing code sharing in the computational biology
 420 community. *PLOS Computational Biology*, 18(6), e1010193. <https://doi.org/10.1371/journal.pcbi.1010193>
- 421 Campbell, T., Dixon, K. W., & Handcock, R. N. (2023). Restoration and replication: A case study on the value of computational
 422 reproducibility assessment. *Restoration Ecology*, 31(8), e13968. <https://doi.org/10.1111/rec.13968>
- 423 Cao, H., Dodge, J., Lo, K., McFarland, D. A., & Wang, L. L. (2023). *The Rise of Open Science: Tracking the Evolution and Perceived*
 424 *Value of Data and Methods Link-Sharing Practices*. arXiv. <https://doi.org/10.48550/arXiv.2310.03193>
- 425 Chalmers, I., & Glasziou, P. (2009). Avoidable waste in the production and reporting of research evidence. *The Lancet*,
 426 374(9683), 86–89. [https://doi.org/10.1016/S0140-6736\(09\)60329-9](https://doi.org/10.1016/S0140-6736(09)60329-9)
- 427 Christian, T.-M., Gooch, A., Vision, T., & Hull, E. (2020). Journal data policies: Exploring how the understanding of editors and
 428 authors corresponds to the policies themselves. *PLOS ONE*, 15(3), e0230281.
 429 <https://doi.org/10.1371/journal.pone.0230281>
- 430 Colavizza, G., Cadwallader, L., LaFlamme, M., Dozot, G., Lecorney, S., Rappo, D., & Hrynaszkiewicz, I. (2024). An analysis of the
 431 effects of sharing research data, code, and preprints on citations. *PLOS ONE*, 19(10), e0311493.
 432 <https://doi.org/10.1371/journal.pone.0311493>
- 433 Cole, N. L., Kormann, E., Klebel, T., Apartis, S., & Ross-Hellauer, T. (2024). The societal impact of Open Science: A scoping review.
 434 *Royal Society Open Science*, 11(6), 240286. <https://doi.org/10.1098/rsos.240286>
- 435 Culina, A., Van Den Berg, I., Evans, S., & Sánchez-Tójar, A. (2020). Low availability of code in ecology: A call for urgent action.
 436 *PLOS Biology*, 18(7), e3000763. <https://doi.org/10.1371/journal.pbio.3000763>
- 437 Donoho, D. L., Maleki, A., Rahman, I. U., Shahram, M., & Stodden, V. (2009). Reproducible Research in Computational Harmonic
 438 Analysis. *Computing in Science & Engineering*, 11(1), 8–18. *Computing in Science & Engineering*.
 439 <https://doi.org/10.1109/MCSE.2009.15>
- 440 Ellis, D. A., Towse, J., Brown, O., Cork, A., Davidson, B. I., Devereux, S., Hinds, J., Ivory, M., Nightingale, S., Parry, D. A., Piwek, L.,
 441 Shaw, H., & Towse, A. S. (2024). Assessing computational reproducibility in Behavior Research Methods. *Behavior*
 442 *Research Methods*, 56(8), 8745–8760. <https://doi.org/10.3758/s13428-024-02501-5>
- 443 Essawy, B. T., Goodall, J. L., Voce, D., Morsy, M. M., Sadler, J. M., Choi, Y. D., Tarboton, D. G., & Malik, T. (2020). A taxonomy for
 444 reproducible and replicable research in environmental modelling. *Environmental Modelling & Software*, 134, 104753.
 445 <https://doi.org/10.1016/j.envsoft.2020.104753>
- 446 European Organization For Nuclear Research. (2013). *Zenodo*. Zenodo. <https://www.zenodo.org/>
- 447 Evans, S. R. (2016). Gauging the Purported Costs of Public Data Archiving for Long-Term Population Studies. *PLOS Biology*, 14(4),
 448 e1002432. <https://doi.org/10.1371/journal.pbio.1002432>
- 449 Feng, X., Qiao, H., & Enquist, B. J. (2020). Doubling demands in programming skills call for ecoinformatics education. *Frontiers in*
 450 *Ecology and the Environment*, 18(3), 123–124. <https://doi.org/10.1002/fee.2179>
- 451 Ferguson, J., Littman, R., Christensen, G., Paluck, E. L., Swanson, N., Wang, Z., Miguel, E., Birke, D., & Pezzuto, J.-H. (2023).
 452 Survey of open science practices and attitudes in the social sciences. *Nature Communications*, 14(1), 5401.
 453 <https://doi.org/10.1038/s41467-023-41111-1>

- 454 Fišar, M., Greiner, B., Huber, C., Katok, E., Ozkes, A. I., & the Management Science Reproducibility Collaboration. (2024).
 455 Reproducibility in *Management Science*. *Management Science*, 70(3), 1343–1356.
 456 <https://doi.org/10.1287/mnsc.2023.03556>
- 457 Gewin, V. (2016). Data sharing: An open mind on open data. *Nature*, 529(7584), 117–119. <https://doi.org/10.1038/nj7584-117a>
- 458 Gomes, D. G. E., Pottier, P., Crystal-Ornelas, R., Hudgins, E. J., Foroughirad, V., Sánchez-Reyes, L. L., Turba, R., Martinez, P. A.,
 459 Moreau, D., Bertram, M. G., Smout, C. A., & Gaynor, K. M. (2022). Why don't we share data and code? Perceived barriers
 460 and benefits to public archiving practices. *Proceedings of the Royal Society B: Biological Sciences*, 289(1987), 20221113.
 461 <https://doi.org/10.1098/rspb.2022.1113>
- 462 Grainger, M. J., Bolam, F. C., Stewart, G. B., & Nilsen, E. B. (2020). Evidence synthesis for tackling research waste. *Nature*
 463 *Ecology & Evolution*, 4(4), 495–497. <https://doi.org/10.1038/s41559-020-1141-6>
- 464 Grüning, B., Chilton, J., Köster, J., Dale, R., Soranzo, N., Van Den Beek, M., Goecks, J., Backofen, R., Nekrutenko, A., & Taylor, J.
 465 (2018). Practical Computational Reproducibility in the Life Sciences. *Cell Systems*, 6(6), 631–635.
 466 <https://doi.org/10.1016/j.cels.2018.03.014>
- 467 Hamilton, D. G., Hong, K., Fraser, H., Rowhani-Farid, A., Fidler, F., & Page, M. J. (2023). Prevalence and predictors of data and
 468 code sharing in the medical and health sciences: Systematic review with meta-analysis of individual participant data.
 469 *BMJ*, 382, e075767. <https://doi.org/10.1136/bmj-2023-075767>
- 470 Henderson, A. S., Hickson, R. I., Furlong, M., McBryde, E. S., & Meehan, M. T. (2024). Reproducibility of COVID-era infectious
 471 disease models. *Epidemics*, 46, 100743. <https://doi.org/10.1016/j.epidem.2024.100743>
- 472 Heumüller, R., Nielebock, S., Krüger, J., & Ortmeier, F. (2020). Publish or perish, but do not forget your software artifacts.
 473 *Empirical Software Engineering*, 25(6), 4585–4616. <https://doi.org/10.1007/s10664-020-09851-6>
- 474 Hinsen, K. (2019). Dealing With Software Collapse. *Computing in Science & Engineering*, 21(3), 104–108.
 475 <https://doi.org/10.1109/MCSE.2019.2900945>
- 476 Ivimey-Cook, E. R., Pick, J. L., Bairos-Novak, K. R., Culina, A., Gould, E., Grainger, M., Marshall, B. M., Moreau, D., Paquet, M.,
 477 Royauté, R., Sánchez-Tójar, A., Silva, I., & Windecker, S. M. (2023). Implementing code review in the scientific workflow:
 478 Insights from ecology and evolutionary biology. *Journal of Evolutionary Biology*, 36(10), 1347–1356.
 479 <https://doi.org/10.1111/jeb.14230>
- 480 Ivimey-Cook, E. R., Sánchez-Tójar, A., Berberí, I., Culina, A., Roche, D. G., Almeida, R. A., Amin, B., Bairos-Novak, K. R., Balti, H.,
 481 Bertram, M., Bliard, L., Byrne, I., Chan, Y.-C., Cioffi, W. R., Corbel, Q., Elsy, A. D., Florko, K. R. N., Gould, E., Grainger, M., ...
 482 Moran, N. P. (2025). *From Policy to Practice: Progress towards Data- and Code-Sharing in Ecology and Evolution*.
 483 *EcoEvoRxiv*. <https://doi.org/10.32942/X2492Q>
- 484 Jay, C., Haines, R., & Katz, D. S. (2021). Software Must be Recognised as an Important Output of Scholarly Research.
 485 *International Journal of Digital Curation*, 16(1), 6. <https://doi.org/10.2218/ijdc.v16i1.745>
- 486 Jenkins, G. B., Beckerman, A. P., Bellard, C., Benítez-López, A., Ellison, A. M., Foote, C. G., Hufton, A. L., Lashley, M. A., Lortie, C.
 487 J., Ma, Z., Moore, A. J., Narum, S. R., Nilsson, J., O'Boyle, B., Provete, D. B., Razgour, O., Rieseberg, L., Riginos, C., Santini,
 488 L., ... Peres-Neto, P. R. (2023). Reproducibility in ecology and evolution: Minimum standards for data and code. *Ecology*
 489 *and Evolution*, 13(5), e9961. <https://doi.org/10.1002/ece3.9961>
- 490 Kambouris, S., Wilkinson, D. P., Smith, E. T., & Fidler, F. (2024). Computationally reproducing results from meta-analyses in
 491 ecology and evolutionary biology using shared code and data. *PLOS ONE*, 19(3), e0300333.
 492 <https://doi.org/10.1371/journal.pone.0300333>
- 493 Kellner, K. F., Doser, J. W., & Belant, J. L. (2024). Functional R code is rare in species distribution and abundance papers.
 494 *Ecology*, e4475. <https://doi.org/10.1002/ecy.4475>
- 495 Kim, A. Y., Herrmann, V., Barreto, R., Calkins, B., Gonzalez-Akre, E., Johnson, D. J., Jordan, J. A., Magee, L., McGregor, I. R.,
 496 Montero, N., Novak, K., Rogers, T., Shue, J., & Anderson-Teixeira, K. J. (2022). Implementing GitHub Actions continuous
 497 integration to reduce error rates in ecological data collection. *Methods in Ecology and Evolution*, 13(11), 2572–2585.
 498 <https://doi.org/10.1111/2041-210X.13982>
- 499 Kohrs, F. E., Auer, S., Bannach-Brown, A., Fiedler, S., Haven, T. L., Heise, V., Holman, C., Azevedo, F., Bernard, R., Bleier, A.,
 500 Bössel, N., Cahill, B. P., Castro, L. J., Ehrenhofer, A., Eichel, K., Frank, M., Frick, C., Friese, M., Gärtner, A., ... Weissgerber,

501 T. L. (2023). Eleven strategies for making reproducible research and open science training the norm at research
502 institutions. *eLife*, 12, e89736. <https://doi.org/10.7554/eLife.89736>

503 Konkol, M., Kray, C., & Pfeiffer, M. (2019). Computational reproducibility in geoscientific papers: Insights from a series of
504 studies with geoscientists and a reproduction study. *International Journal of Geographical Information Science*, 33(2),
505 408–429. <https://doi.org/10.1080/13658816.2018.1508687>

506 Krafczyk, M. S., Shi, A., Bhaskar, A., Marinov, D., & Stodden, V. (2021). Learning from reproducing computational results:
507 Introducing three principles and the *Reproduction Package*. *Philosophical Transactions of the Royal Society A:
508 Mathematical, Physical and Engineering Sciences*, 379(2197), rsta.2020.0069, 20200069.
509 <https://doi.org/10.1098/rsta.2020.0069>

510 Lai, J., Lortie, C. J., Muenchen, R. A., Yang, J., & Ma, K. (2019). Evaluating the popularity of R in ecology. *Ecosphere*, 10(1),
511 e02567. <https://doi.org/10.1002/ecs2.2567>

512 Lasser, J. (2020). Creating an executable paper is a journey through Open Science. *Communications Physics*, 3(1), 143.
513 <https://doi.org/10.1038/s42005-020-00403-4>

514 Laurinavichyute, A., Yadav, H., & Vasishth, S. (2022). Share the code, not just the data: A case study of the reproducibility of
515 articles published in the Journal of Memory and Language under the open data policy. *Journal of Memory and Language*,
516 125, 104332. <https://doi.org/10.1016/j.jml.2022.104332>

517 Lewis, K. P., Vander Wal, E., & Fifield, D. A. (2018). Wildlife biology, big data, and reproducible research. *Wildlife Society
518 Bulletin*, 42(1), 172–179. <https://doi.org/10.1002/wsb.847>

519 Maitner, B., Santos Andrade, P. E., Lei, L., Kass, J., Owens, H. L., Barbosa, G. C. G., Boyle, B., Castorena, M., Enquist, B. J., Feng,
520 X., Park, D. S., Paz, A., Pinilla-Buitrago, G., Merow, C., & Wilson, A. (2024). Code sharing in ecology and evolution
521 increases citation rates but remains uncommon. *Ecology and Evolution*, 14(8), e70030.
522 <https://doi.org/10.1002/ece3.70030>

523 McKiernan, E. C. (2017). Imagining the “open” university: Sharing scholarship to improve research and education. *PLOS Biology*,
524 15(10), e1002614. <https://doi.org/10.1371/journal.pbio.1002614>

525 Mislan, K. A. S., Heer, J. M., & White, E. P. (2016). Elevating The Status of Code in Ecology. *Trends in Ecology & Evolution*, 31(1),
526 4–7. <https://doi.org/10.1016/j.tree.2015.11.006>

527 Nguyen, P., McKenzie, J. E., Hamilton, D. G., Moher, D., Tugwell, P., Fidler, F. M., Haddaway, N. R., Higgins, J. P. T., Kanukula, R.,
528 Karunanathan, S., Maxwell, L. J., McDonald, S., Nakagawa, S., Nunan, D., Welch, V. A., & Page, M. J. (2023). Systematic
529 reviewers’ perspectives on sharing review data, analytic code, and other materials: A survey. *Cochrane Evidence
530 Synthesis and Methods*, 1(2), e12008. <https://doi.org/10.1002/cesm.12008>

531 Obels, P., Lakens, D., Coles, N. A., Gottfried, J., & Green, S. A. (2020). Analysis of Open Data and Computational Reproducibility
532 in Registered Reports in Psychology. *Advances in Methods and Practices in Psychological Science*, 3(2), 229–237.
533 <https://doi.org/10.1177/2515245920918872>

534 O’Dea, R. E., Lagisz, M., Jennions, M. D., Koricheva, J., Noble, D. W. A., Parker, T. H., Gurevitch, J., Page, M. J., Stewart, G.,
535 Moher, D., & Nakagawa, S. (2021). Preferred reporting items for systematic reviews and meta-analyses in ecology and
536 evolutionary biology: A PRISMA extension. *Biological Reviews*, 96(5), 1695–1722. <https://doi.org/10.1111/brv.12721>

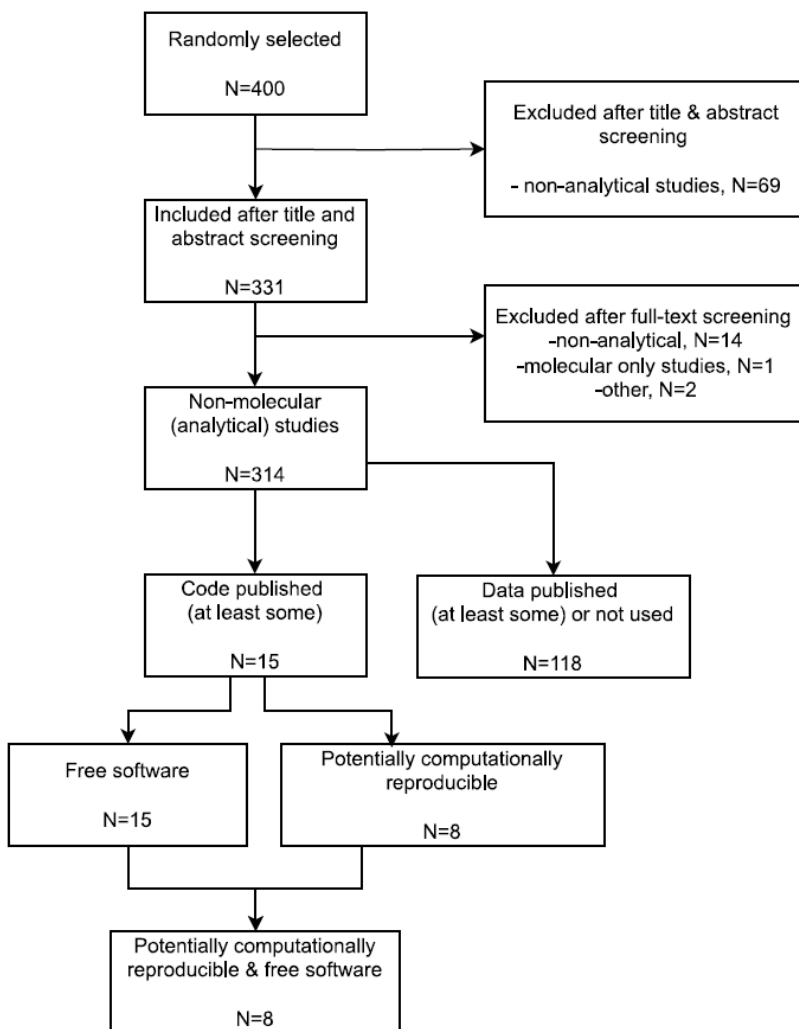
537 Ostermann, F. O., & Granell, C. (2017). Advancing Science with VGI: Reproducibility and Replicability of Recent Studies using
538 VGI. *Transactions in GIS*, 21(2), 224–237. <https://doi.org/10.1111/tgis.12195>

539 Ouzzani, M., Hammady, H., Fedorowicz, Z., & Elmagarmid, A. (2016). Rayyan—A web and mobile app for systematic reviews.
540 *Systematic Reviews*, 5(1), 210. <https://doi.org/10.1186/s13643-016-0384-4>

541 Page, M. J., Nguyen, P.-Y., Hamilton, D. G., Haddaway, N. R., Kanukula, R., Moher, D., & McKenzie, J. E. (2022). Data and code
542 availability statements in systematic reviews of interventions were often missing or inaccurate: A content analysis.
543 *Journal of Clinical Epidemiology*, 147, 1–10. <https://doi.org/10.1016/j.jclinepi.2022.03.003>

544 Peng, R. D. (2011). Reproducible Research in Computational Science. *Science*, 334(6060), 1226–1227.
545 <https://doi.org/10.1126/science.1213847>

- 546 Purgar, M., Glasziou, P., Klanjscek, T., Nakagawa, S., & Culina, A. (2024). Supporting study registration to reduce research waste.
547 *Nature Ecology & Evolution*, 8(8), 1391–1399. <https://doi.org/10.1038/s41559-024-02433-5>
- 548 Purgar, M., Klanjscek, T., & Culina, A. (2022). Quantifying research waste in ecology. *Nature Ecology & Evolution*, 6(9), 1390–
549 1397. <https://doi.org/10.1038/s41559-022-01820-0>
- 550 R Core Team. (2023). *R: A language and environment for statistical computing* [Computer software]. R Foundation for Statistical
551 Computing. <https://www.R-project.org/>
- 552 Roche, D. G., Berberi, I., Dhane, F., Lauzon, F., Soeharjono, S., Dakin, R., & Binning, S. A. (2022). Slow improvement to the
553 archiving quality of open datasets shared by researchers in ecology and evolution. *Proceedings of the Royal Society B:*
554 *Biological Sciences*, 289(1975), 20212780. <https://doi.org/10.1098/rspb.2021.2780>
- 555 Roche, D. G., Kruuk, L. E. B., Lanfear, R., & Binning, S. A. (2015). Public Data Archiving in Ecology and Evolution: How Well Are
556 We Doing? *PLOS Biology*, 13(11), e1002295. <https://doi.org/10.1371/journal.pbio.1002295>
- 557 Roche, D. G., Raby, G. D., Norin, T., Ern, R., Scheuffele, H., Skeeles, M., Morgan, R., Andreassen, A. H., Clements, J. C., Louissaint,
558 S., Jutfelt, F., Clark, T. D., & Binning, S. A. (2022). Paths towards greater consensus building in experimental biology.
559 *Journal of Experimental Biology*, 225(Suppl_1), jeb243559. <https://doi.org/10.1242/jeb.243559>
- 560 Rodriguez-Sanchez, F., & Jackson, C. P. (2024). *grateful: Facilitate citation of R packages*. [Computer software].
561 <https://pakillo.github.io/grateful/>
- 562 Samuel, S., & Mietchen, D. (2024). Computational reproducibility of Jupyter notebooks from biomedical publications.
563 *GigaScience*, 13, giad113. <https://doi.org/10.1093/gigascience/giad113>
- 564 Sánchez-Tójar, A., Bezine, A., Purgar, M., & Culina, A. (2025). *Data and Code for 'Code-sharing policies are associated with*
565 *increased reproducibility potential of ecological findings'* (Version v.2.0.0) [Computer software]. Zenodo.
566 <https://doi.org/10.5281/zenodo.15077314>
- 567 Serghiou, S., Contopoulos-Ioannidis, D. G., Boyack, K. W., Riedel, N., Wallach, J. D., & Ioannidis, J. P. A. (2021). Assessment of
568 transparency indicators across the biomedical literature: How open is open? *PLOS Biology*, 19(3), e3001107.
569 <https://doi.org/10.1371/journal.pbio.3001107>
- 570 Sharma, N. K., Ayyala, R., Deshpande, D., Patel, Y., Munteanu, V., Ciorba, D., Bostan, V., Fiscutean, A., Vahed, M., Sarkar, A.,
571 Guo, R., Moore, A., Darci-Maher, N., Nogoy, N., Abedalthagafi, M., & Mangul, S. (2024). Analytical code sharing practices
572 in biomedical research. *PeerJ Computer Science*, 10, e2066. <https://doi.org/10.7717/peerj-cs.2066>
- 573 Soeharjono, S., & Roche, D. G. (2021). Reported Individual Costs and Benefits of Sharing Open Data among Canadian Academic
574 Faculty in Ecology and Evolution. *BioScience*, 71(7), 750–756. <https://doi.org/10.1093/biosci/biab024>
- 575 Sperandii, M. G., Bazzichetto, M., Mendieta-Leiva, G., Schmidlein, S., Bott, M., de Lima, R. A. F., Pillar, V. D., Price, J. N.,
576 Wagner, V., & Chytrý, M. (2024). Towards more reproducibility in vegetation research. *Journal of Vegetation Science*,
577 35(1), e13224. <https://doi.org/10.1111/jvs.13224>
- 578 Tan, A. C., Webster, A. C., Libesman, S., Yang, Z., Chand, R. R., Liu, W., Palacios, T., Hunter, K. E., & Seidler, A. L. (2024). Data
579 sharing policies across health research globally: CROSS-sectional meta-research study. *Research Synthesis Methods*, 15(6),
580 1060–1071. <https://doi.org/10.1002/jrsm.1757>
- 581 Touchon, J. C., & McCoy, M. W. (2016). The mismatch between current statistical practice and doctoral training in ecology.
582 *Ecosphere*, 7(8), e01394. <https://doi.org/10.1002/ecs2.1394>
- 583 Trisovic, A., Lau, M. K., Pasquier, T., & Crosas, M. (2022). A large-scale study on research code quality and execution. *Scientific*
584 *Data*, 9(1), 60. <https://doi.org/10.1038/s41597-022-01143-6>
- 585 Venkatesh, K., Santomartino, S. M., Sulam, J., & Yi, P. H. (2022). Code and Data Sharing Practices in the Radiology
586 Artificial Intelligence Literature: A Meta-Research Study. *Radiology: Artificial Intelligence*, 4(5), e220081.
587 <https://doi.org/10.1148/ryai.220081>
- 588 Wickham, H. (2016). *ggplot2: Elegant Graphics for Data Analysis* (2nd ed.). Springer Cham. <https://ggplot2.tidyverse.org>
- 589



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591 **Figure S1.** PRISMA diagram detailing the screening procedure and final number of articles included.