# 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. 2024).

## 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

## Introduction

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

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

Code-sharing does not necessarily translate into code that is easy to understand, adapt, and reuse. Multiple technical challenges to code reuse range from dependencies on the original researcher's computational environment, such as the operating system and libraries used, to inadequate documentation on how to install, run, and use the code (Boettiger 2015). Code can also easily *rot* after software updates, leading to changes in functionality, compatibility, and, ultimately, the reproducibility of the results (Hinsen 2019). Although container technology such as Docker, which packages software and its dependencies into a standardized environment, has been suggested as a solution to improve portability and reproducibility (Boettiger 2015; Grüning et al. 2018; Essawy et al. 2020; Trisovic et al. 2022), its adoption remains low (e.g., Venkatesh et al. 2022). At the minimum, the software and packages that are fundamental for the analyses should be stated and appropriately referenced in the main manuscript, and the version(s) used should be clearly stated (guidelines for software citation: Chue Hong et al. 2019). The remaining packages should be documented as part of stand-alone documentation (e.g., README, or inline comments; Benureau and Rougier 2018; Jenkins et al. 2023; Ivimey-Cook et al. 2023). Software and package citation is important for computational reproducibility but also to better explain the methodology and give credit to software developers. In addition, the code should ideally be written using free (i.e., non-proprietary) and open-source software (also known as FOSS; Ostermann and Granell 2016) such as the free and open-source R programming language (R Core Team 2023) which is widely used in ecology (Lai et al. 2019; Culina et al. 2020; Kambouris et al. 2024). Furthermore, code should be shared in a permanent repository (e.g., Zenodo) and assigned an open and permissive licence and a persistent identifier such as a DOI (Krafczyk et al. 2021; Kim et al. 2022; Jenkins et al. 2023). This is particularly important given the far-from-ideal rates of link persistence found for scientific code in fields such as astrophysics (Allen et al. 2018; Sperandii et al. 2024).

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

## Methods

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

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

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

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

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

## Results

Code- and data-sharing

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

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

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

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

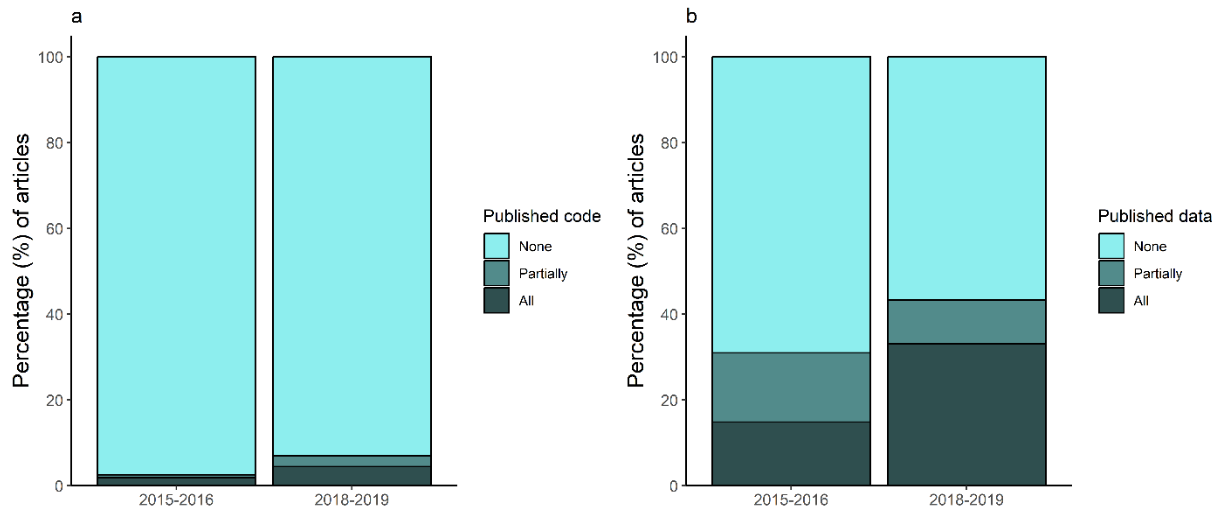


**Figure 1**. Code- and data-sharing are uncommon in 12 ecological journals without a code-sharing policy. Percentage of nonmolecular articles surveyed that provided code (a)or data (b) for each of the periods studied (2015–2016: 157 articles, 2018–2019: 157 articles).

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

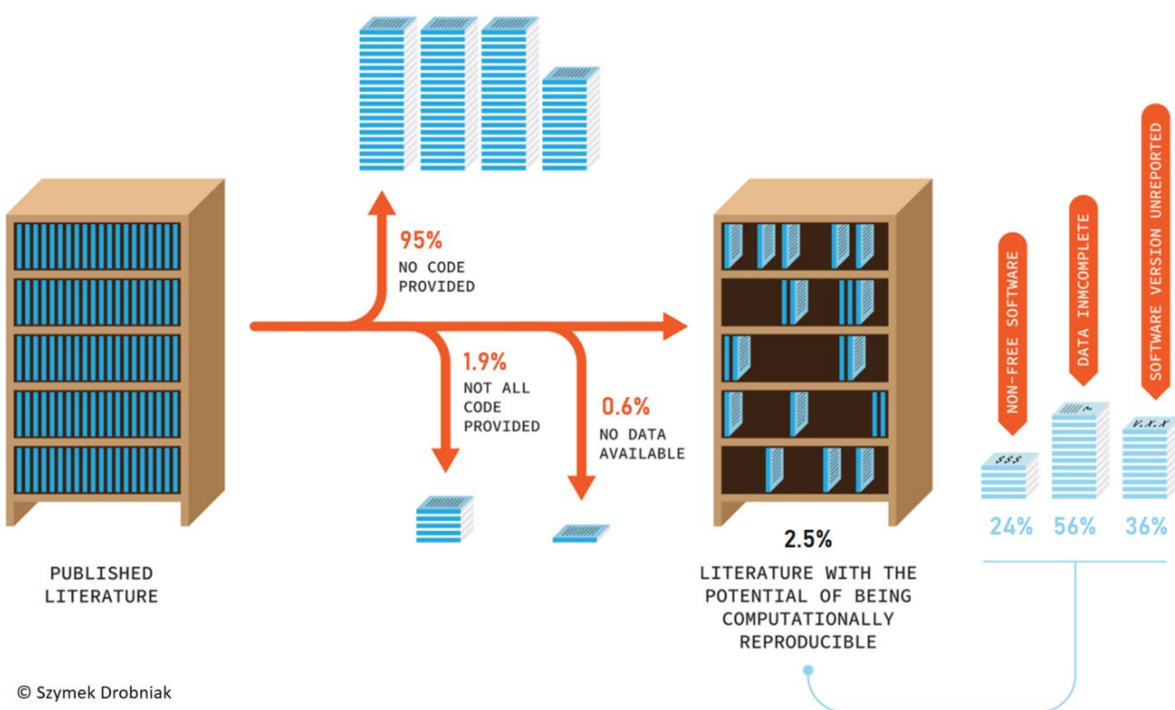


**Figure 2**. Diagram visually representing the computational reproducibility potential of articles published between 2015 and 2019 in ecological journals without a code-sharing policy. The value corresponding to “Data incomplete”

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

<u>Features boosting long-term reproducibility in journals with and without a code-sharing policy</u>

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

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

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

## Discussion

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

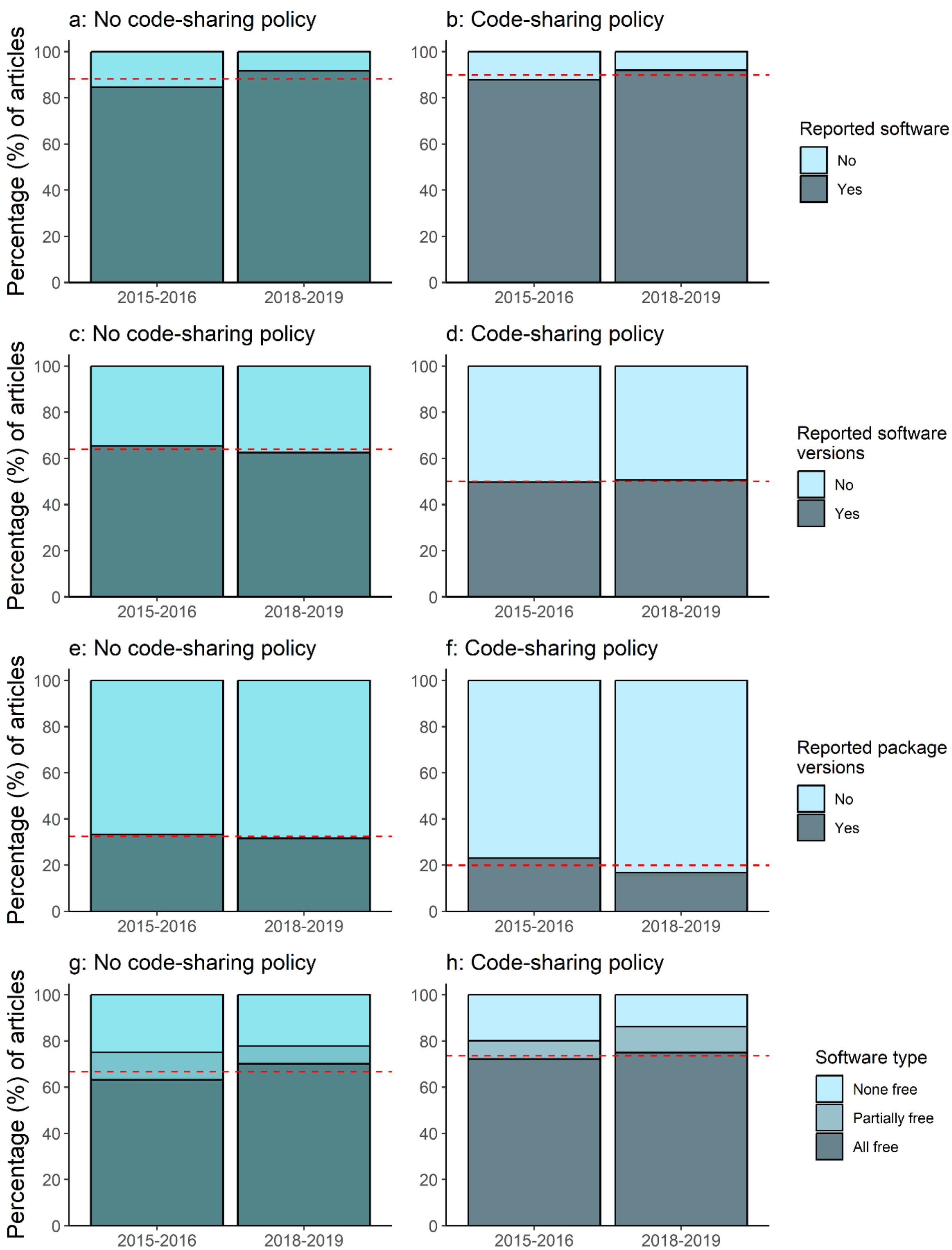


**Figure 3**. Features boosting long-term reproducibility in journals with (b, d, f, h; right-hand side panels) and without a code-sharing policy (a, c, e, g; left-hand side panels). The red dashed line corresponds to the mean for the category coloured in black (i.e., No software reported, Software versions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

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

**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).

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

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

We found that features boosting long-term reproducibility, such as using free software and reporting its version, were similar between journals with and without a code-sharing policy, suggesting that, although code-sharing policies seem to increase code availability, they might not increase software reporting without being more explicit about best practices. We found that versions of the statistical software and packages were often missing, and approximately a tenth of the articles did not even state the software used. Reporting software and package versions is important for several reasons. First, they can help to understand and solve technical issues related to software dependencies, which are among the most frequently encountered factors hindering computational reproducibility (Laurinavichyute et al. 2022; Kellner et al. 2024; Samuel and Mietchen 2024). Different versions of software and/or packages can lead to inconsistencies in results and even to code rot, which occurs when the code relies on specific versions of software or packages that are no longer available or have undergone significant changes (e.g., deprecated functions), rendering the code incompatible with current operating systems (Boettiger 2015; Laurinavichyute et al. 2022). Second, software reporting standards are key for computational reproducibility (i.e., obtaining the same results using the same input data and code) but also for analytical reproducibility (i.e., obtaining the same results writing *fresh code* using the provided written methodological descriptions when data but not code are available; Kambouris et al. 2024), and thus should be prioritized by authors and journals alike (Box 1). Finally, about one-fifth of the articles exclusively used non-free (i.e., proprietary) software. Reproducibility is hindered when the code relies on proprietary software that requires license or subscriptions. Proprietary software restricts access to its source code and is inaccessible to researchers who cannot afford it, ultimately limiting independent verification and building upon original research (Ostermann and Granell 2016; Benureau and Rougier 2018; Konkol et al. 2019; Laurinavichyute et al. 2022). Ideally, the code used for a study should be peer reviewed to ensure its completeness, reusability, and reproducibility prior to manuscript acceptance (Ivimey-Cook et al. 2023). Before code review becomes a norm, authors, reviewers, and editors should ensure that the minimum requirements for reproducibility are met, which can be facilitated by the use of checklists and policies explicitly linked to best practices. In addition, we advocate for proper software and package citation to give credit to software developers and incentivise software and package development (e.g., using the R package 'grateful'; Rodriguez-Sanchez and Jackson 2024).

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

## Conclusions

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

## Authors contributions

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

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## Competing interest

Alfredo Sánchez-Tójar, Marija Purgar, and Antica Culina are officers of the Society for Open, Reliable, and Transparent Ecology and Evolutionary Biology (SORTEE). Aya Bezine declares no competing interests.

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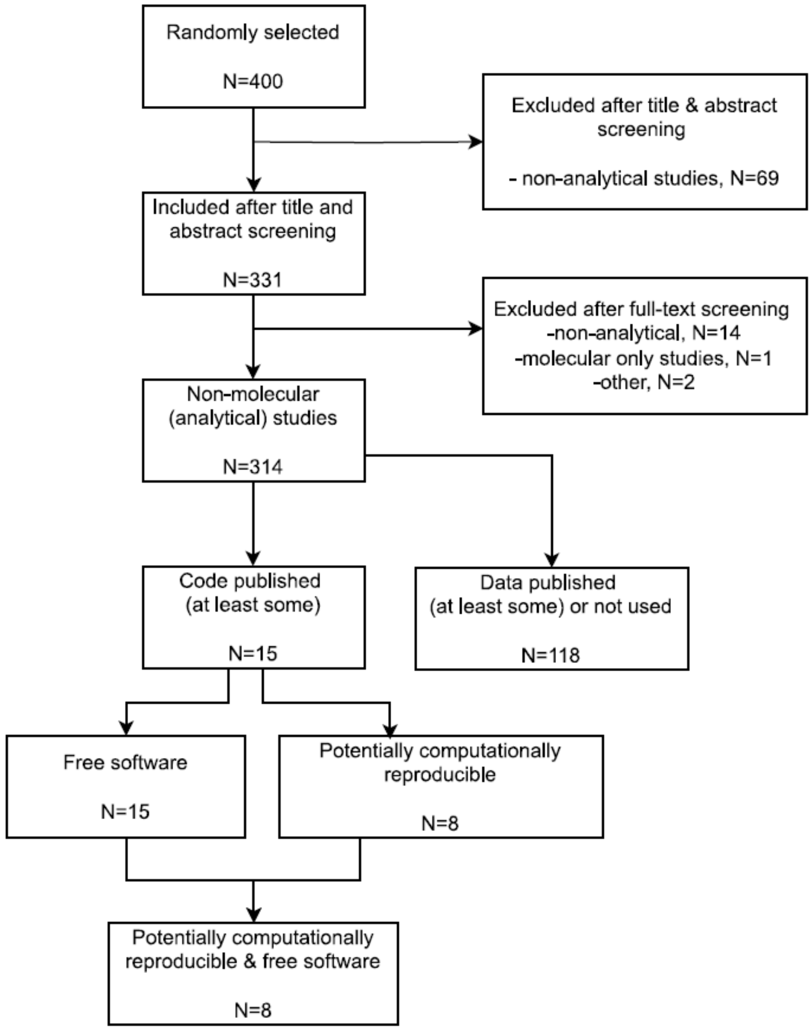


**Figure S1**. PRISMA diagram detailing the screening procedure and final number of articles included.