

1 **Do We Have a Reproducibility Crisis: How Available is Data and Code**
2 **Across Journals in Artificial Intelligence and Earth Sciences?**

3 Erin A. Jones^a, Brandon McClung^a, Hadi Fawad^c, Amy McGovern^{a,b,c}

4 ^a *School of Meteorology, University of Oklahoma, Norman OK USA*

5 ^b *NSF AI Institute for Research on Trustworthy AI in Weather, Climate, and Coastal*
6 *Oceanography (AI2ES), USA*

7 ^c *School of Computer Science, University of Oklahoma, Norman OK USA*

8 *Corresponding author: amcgovern@ou.edu*

9 ABSTRACT: As the use of artificial intelligence (AI) has grown exponentially across a wide
10 variety of science applications, it has become clear that it is critical to share data and code to
11 facilitate reproducibility. AMS recently adopted the requirement that all papers include a data
12 availability statement. However, there is no requirement to ensure that the data and code are openly
13 accessible during and after publication. Studies show that without this requirement, data is openly
14 available in about one third of journal articles. In this work, we surveyed two AMS journals, AIES
15 and MWR, and two non-AMS journals, considering the following research questions. First, to
16 what extent are the data and code stated to be available in AIES journal articles? Second, how do
17 these results compared to articles in 1) MWR, an AMS journal without a primary focus on AI;
18 2) a non-AMS journal with a data availability statement requirement focused on AI but not Earth
19 sciences; and 3) a non-AMS journal focused on AI in Earth sciences without a data availability
20 statement requirement? Third, for the papers which claim to have openly accessible data and code,
21 can readers easily access the data and code? Finally, what are the justifications that are provided
22 for articles that have a data availability statement but do not provide open access to their data or
23 code?

24 SIGNIFICANCE STATEMENT: Making code and data available to future researchers is critical
25 for research reproducibility. Despite this, if it is not required, authors share their code and data
26 only about one third of the time. We show that even with the new AMS journal requirement to
27 include a data availability statement, the actual availability is limited. This issue is important to
28 address for future research, and especially with the growing research in AI. If data and models are
29 made easily available, people can innovate on these models in a more equitable manner.

30 **1. Introduction**

31 There has been a recent rapid acceleration of growth of the use of artificial intelligence (AI)—both
32 as a tool in Earth science research as well as in society as a whole (e.g., Haupt et al. 2022; Stall
33 et al. 2023; Maslej et al. 2024). AI tools increasingly have complex architectures, which may
34 be a barrier for scientific innovation and reproducibility (e.g., Pineau et al. 2021; Liesenfeld and
35 Dingemanse 2024). These tools also rely on copious amounts of training data, which rely on
36 the producers of the AI to have sourced ethically and without bias (e.g., McGovern et al. 2024;
37 Wirz et al. 2024). Increased transparency, however, may be obtained through the documentation
38 and open sharing of training data, pre-processing and model code, and any associated metadata.
39 The availability of shared resources expedites collaborative efforts, which is essential for tackling
40 multifaceted challenges with global societal impacts (e.g., Stall et al. 2023).

41 Recently, AMS journals adopted a policy with the expectation that a data availability statement
42 (DAS) accompanies every published article¹. AMS is not alone in this expectation. Internationally,
43 science is becoming more open (e.g., Grant and Hrynaszkiewicz 2018; Graf et al. 2020; UNESCO
44 2021; Bertram et al. 2023). Several ethical guidelines have been developed to help scientists
45 navigate making their research more open (e.g., Goodman et al. 2014; Fecher and Friesike 2014).
46 AMS, specifically, cites the FAIR (Findable, Accessible, Interoperable, and Reusable) Guiding
47 Principles (Wilkinson et al. 2016) in their commitment to open data². These principles suggest not
48 only that datasets and code are easily available, but also that they are supplemented with appropriate
49 documentation and metadata so that any research conducted using them can be reproduced.

¹[https://www.ametsoc.org/index.cfm/ams/publications/ethical-guidelines-and-ams-policies/
data-and-software-policy-guidelines-for-ams-publications/](https://www.ametsoc.org/index.cfm/ams/publications/ethical-guidelines-and-ams-policies/data-and-software-policy-guidelines-for-ams-publications/)

²[https://www.ametsoc.org/index.cfm/ams/about-ams/ams-statements/statements-of-the-ams-in-force/
full-open-and-timely-access-to-data](https://www.ametsoc.org/index.cfm/ams/about-ams/ams-statements/statements-of-the-ams-in-force/full-open-and-timely-access-to-data)

50 Although a DAS is required by AMS policy, fully open data or code is only recommended and
51 it is up to the individual reviewers to enforce that the data URLs provided are valid. Without a
52 specific requirement to make data openly available, studies have found that only about a third to
53 a half of published works with required DASs have open data (Grant and Hrynaszkiewicz 2018;
54 McGuinness and Sheppard 2021; Tedersoo et al. 2021; Campbell and Mu 2023).

55 Given the rapid advances being made in AI, including within the atmospheric and related science
56 community, we will focus our study on DASs from four journals in the fields of AI and/or Earth
57 Science. First, we will examine DASs from the AMS journal, Artificial Intelligence for the Earth
58 Systems (AIES) to determine the level of data and code availability provided. To compare AMS
59 journals with varying research foci, we will also examine DASs from Monthly Weather Review
60 (MWR), which does not have a primary focus on AI applications. Additionally, we will examine two
61 non-AMS journals: Artificial Intelligence in Geosciences (AI in Geo.) and Artificial Intelligence
62 (AIJ). Similar to AIES, AI in Geo. also has a focus on AI applications in Earth Sciences. However,
63 it does not have a DAS requirement, allowing us to examine the impact of such a requirement.
64 AIJ has a similar DAS requirement to AMS journals. Additionally, AIJ has a primary focus on
65 advancements of AI without concentrating on Earth Science applications, allowing for further
66 comparisons to be made across primary disciplines.

67 **2. Data and Methods**

68 For each journal, the years and number of articles examined are given in Table 1. Given the
69 relatively limited repertoire of AIES and in AI in Geo., all articles published before 15 April 2024
70 and their associated DASs were examined. MWR and AIJ each have a much larger yearly and total
71 number of articles. Therefore, only a sample of articles were examined for each journal.

72 For each article, we collected and recorded the metadata and general information about topic
73 of each article as well as categorized the information about data and/or code (DaCo, hereafter)
74 availability in the DAS, if one was provided. Data availability was categorized as follows: 1) all
75 data openly available; 2) at least some data openly available; 3) data available upon request; 4) no
76 data produced; 5) data not available; 6) no DAS provided. All DASs were subjectively categorized.
77 For example, if it was not clearly stated that some data were not openly available, the DAS was
78 likely placed in category 1. Code was categorized similarly, except the “available upon request”

TABLE 1. Description of journals and number of articles for each journal belonging to each DAS category.

	AIES	AI in Geo	MWR	AIJ
Publisher	AMS Journals	KeAi Publishing	AMS Journals	Elsevier
Online Distribution Platform	AMS Journals	ScienceDirect	AMS Journals	ScienceDirect
Years analyzed	2022-2024	2020-2024	2023	2023-2024
Total articles examined	107	72	54	55
Articles with DASs	107	21	53	55
All data available	76	12	25	12
Some data available	14	1	10	0
Data available upon request	4	5	11	9
No data produced	8	1	0	30
No data available	5	2	7	4
No DAS	0	51	1	0
All code available	56	3	13	15
Some code available	2	0	1	0
No code produced	8	1	0	30
No code available	41	17	39	10
Articles without broken links	84	11	34	12
Articles with broken links	10	3	8	3

category was not separately analyzed. If the DAS claimed DaCo was available, we further recorded its accessibility, such as if any links in the DAS were broken or led to unrelated websites. Finally, if the any DaCo was unavailable, we noted any stated justification.

3. To what extent is data openly shared?

In AIES, all 107 articles examined were submitted after the AMS mandate that every article contain a DAS. Of those articles, 84.1% claimed to make some or all of the data used and produced by the study openly available (Fig. 1a). The DASs of an additional 7.5% of articles claim that their associated work did not utilize any datasets or produce any data. These articles were largely “Perspectives,” “Review,” or “Lessons Learned” article types. Only 3.7% and 4.7% of DASs state that data are available upon request or not available respectively. The proportion of articles with data available is larger than the approximately third to half of all articles found in prior literature (Grant and Hrynaskiewicz 2018; McGuinness and Sheppard 2021; Tedersoo et al. 2021; Campbell and Mu 2023).

We also examined all articles published in AI in Geo. as another journal with a focus on AI in Earth Science, though not frequently atmospheric science. As AI in Geo. does not require a

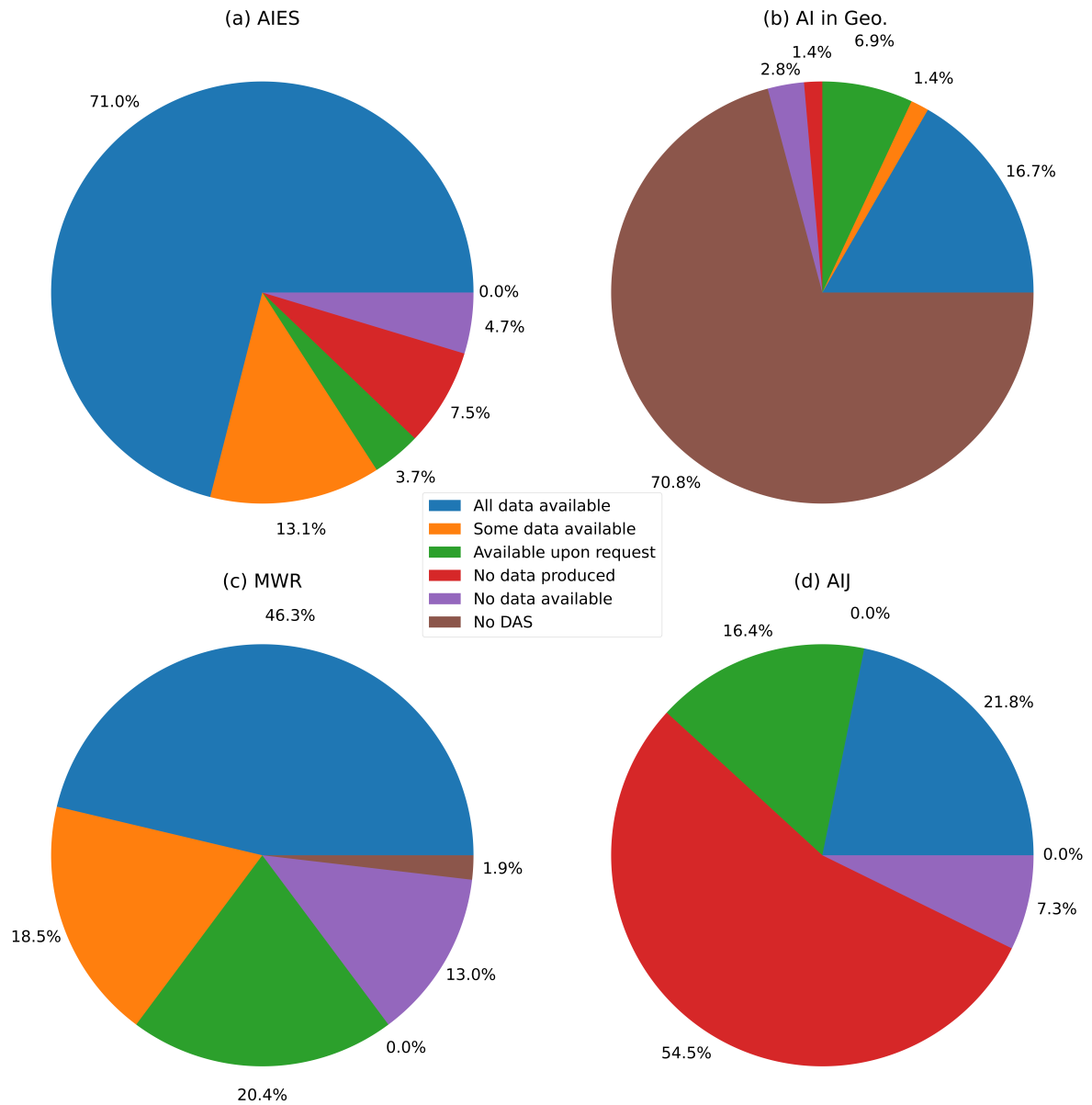


FIG. 1. Proportion of open availability of data for (a) AIES, (b) AI in Geo., (c) MWR, and (d) AIJ.

94 DAS to be submitted with the publication, 70.8% of articles did not include one (Fig. 1b). Of the
 95 remaining articles examined, however, 14 out of 21 had at least some data openly available or no
 96 data produced. Only 2 DASs did not make any data available. Additionally, although there was
 97 no DAS requirement at any point, the percentage of articles with a DAS in increased steadily from
 98 2021 through 2023 and was on track to further increase in 2024 (not shown).

99 Compared to AIES, the 54-article sample chosen for analysis from MWR has a slightly smaller
100 percentage of journals with some or all data openly available at 64.8% (Fig. 1c). Around 20.4%
101 of DASs stated that data would be made available upon request; 14.9% of articles did not make
102 data available, including one article that did not include a DAS as it was first submitted prior to the
103 enforcement of the DAS requirement. The percentage of non-available data is substantially larger
104 for MWR compared to AIES. MWR often publishes research involving large numerical modelling
105 or data assimilation experiments, where dataset size may be unfeasible to store and maintain openly.
106 Although authors should strive for as much open availability as possible, following guidance for
107 the publication of model data such as in Schuster et al. (2023), this reasoning may explain some of
108 increase in non-availability compared to AIES.

109 Slightly over half of our AIJ articles examined were pure theory and review papers, so no data
110 were produced for these articles (Fig. 1d). Of the remaining 25 articles, 12 DASs made all data
111 openly available; 9 DASs made data available upon request; and 4 DASs did not describe openly
112 available data.

113 When DASs were present and data were produced for the study, at least some data were stated
114 to be openly available in more than half of the DASs examined for each journal and more than
115 three quarters as a total between all journals. This result is a larger estimate compared to prior
116 literature (Grant and Hrynaszkiwicz 2018; McGuinness and Sheppard 2021; Tedersoo et al. 2021;
117 Campbell and Mu 2023). Though the specific reason for this discrepancy is beyond the scope of
118 this article, these results are potentially indicating a cultural shift in the perceived value of open
119 data.

120 **4. Is code openly shared to the same extent as data?**

121 Just over half of the DASs in AIES provided links to openly available code (Fig. 2a). AI in
122 Geo. and MWR similarly have substantially fewer DASs providing code than data at around 5%
123 and around 25% of all articles examined respectively (Fig. 2b,c). In AI applications, providing
124 code for the model along with any training pipelines and post-processing steps are just as essential
125 as providing training datasets for scientific reproducibility and transparency (e.g., Liesenfeld and
126 Dingemanse 2024). Similarly, open access to numerical model, data assimilation, post-processing,
127 and/or statistical verification code is also as important as data used or produced. Although, in their

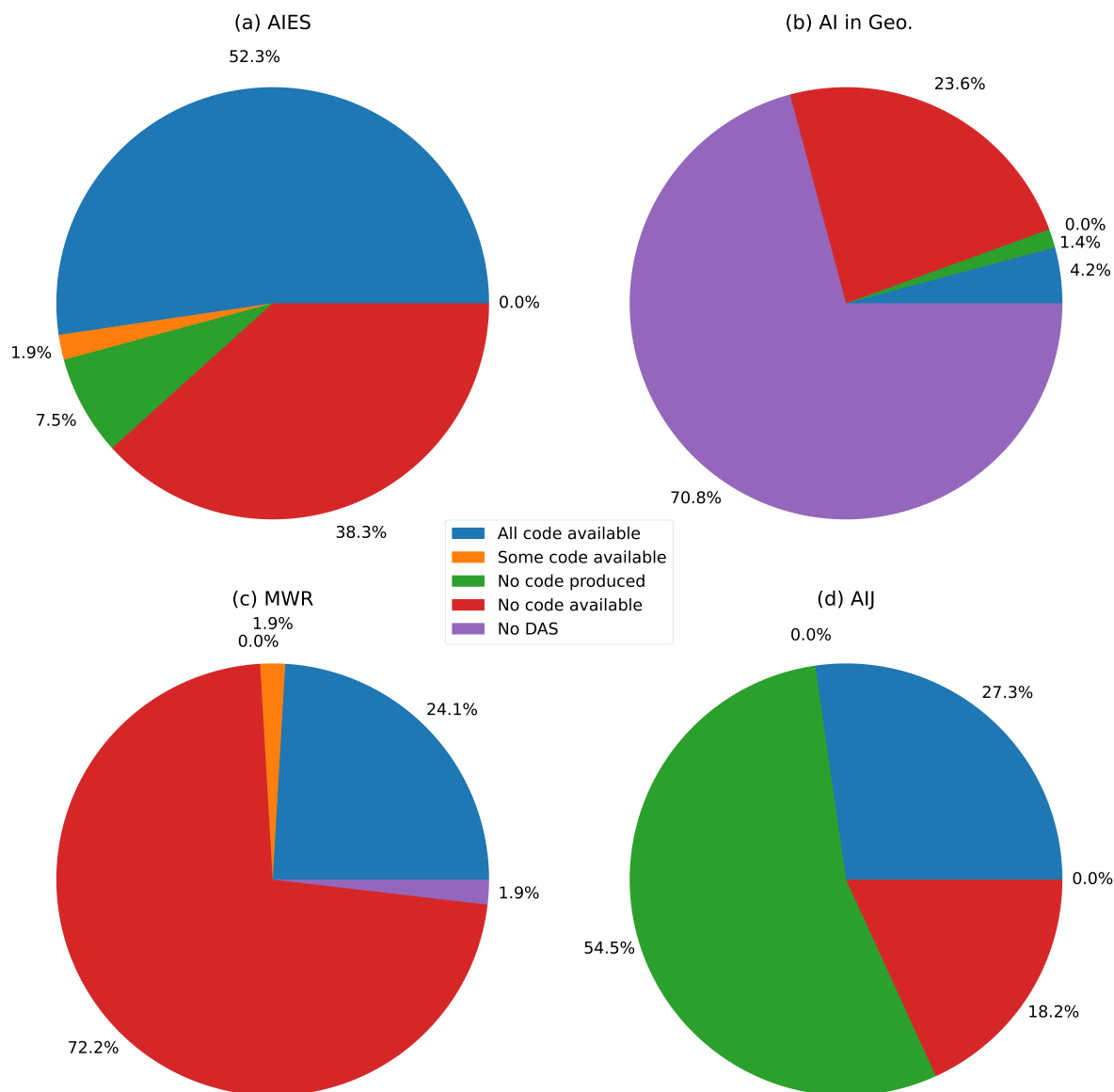


FIG. 2. As in Fig. 1 but for open availability of code.

128 guidelines, AMS indicates that any software used or produced for the articles published should
 129 have a reference and a link provided, authors may not consider providing software as essential in a
 130 “data” availability statement. Additionally, there may not be consistent enforcement of this policy
 131 between AMS journals.

132 Contrasting from the three journals focused on Earth Science applications, AIJ has a larger
 133 proportion of articles that provide open code—at 15 out of the 25 articles where DaCo is pro-

134 duced—compared to open data—at 12 out of 25 articles. This difference may indicate some
135 contrasting culture in what is meant by “open” and what is most valuable to share in research with
136 a focus on Earth Science compared to solely AI.

137 **5. Is “open” data or code actually accessible?**

138 For Figs. 1-2, we examined the DASs for stated availability of data and code. Even if data and
139 code were stated to be available, they may not be easily accessible. In an examination of research
140 produced from a single university, Briney (2024) noted that approximately 5% of links to data were
141 no longer available, making it difficult or impossible for readers to access supposedly open data.
142 The study also noted that the percentages of unavailable links increased with time from the initial
143 publication of the data.

144 In our examination of the 216 DASs in this study, we also determined how many DASs included
145 links to DaCo repositories. We verified each link provided to determine if it directed the reader to
146 the repository or if the link was ‘broken’ and did not lead to a currently established webpage. We
147 determined that 165 DASs included at least one link to a DaCo repository of which approximately
148 15% contained at least one broken link (Table 1). Out of the four journals AIES had the smallest
149 proportion of broken links at approximately 11% of articles.

150 In addition, throughout our examination of links, we found that the web page to which a link
151 directed often did not lead directly to a DaCo repository. Such links frequently led to project or
152 agency home pages, where the DaCo was not easily accessible or occasionally not findable at all.
153 While directing a reader to these home pages may be useful to establish context about a code or
154 dataset, these types of links should not be provided in substitution for direct links.

155 It may, therefore, be prudent for AMS and other journal publishers to create policies to ensure
156 during the review process that any links that claim to point readers to code or dataset actually send
157 readers as directly as possible. Additionally, a periodic examination for broken links in all DASs
158 would help to ensure that data and code remain open as intended for all readers.

159 **6. What are common justifications for not having openly available data or code?**

160 For every DAS that partially or fully did not provide open availability to DaCo, we recorded
161 whether a justification was given for why there was unavailability. If a justification was given, we

175 justification provides insight into what challenges need to be overcome in order to provide fully
176 open DaCo with each.

177 **7. What recommendations do we suggest to further promote open science?**

178 *a. For authors?*

179 Regardless of the requirements of the journal, we recommend that authors provide a DAS with
180 their manuscript. DASs aid in allowing for reproducibility and advancement of science as well as
181 enhancing trust with readers. Trust is especially important in rapidly advancing and broad-impact
182 fields, such as AI. The DAS should provide links to repositories where readers can access any
183 DaCo used or produced for the article. Within the repositories, authors should provide metadata
184 and documentation so that the DaCo is interoperable and reusable for further research purposes
185 (e.g., Edwards et al. 2011). The repositories should be maintained so that the link associated with
186 them stays active. Preferably, a Digital Object Identifier (DOI) should be obtained as typically,
187 these have greater digital permanence than a general URL (Briney 2024). Authors should check
188 the repositories with their DaCo periodically. If any links change, they should contact any journals
189 publishing articles containing such links. If there is some limitation to the open publication of
190 any DaCo, authors should still provide any DaCo they are able. Additionally, these authors should
191 clearly provide justification within their DAS for what is not available and provide clear directions
192 for obtaining any DaCo that may be accessed by some means (e.g., by sending a request to a
193 government agency) but not open to all.

194 *b. For research journal publishers?*

195 The onus of open science should not be solely on the authors. Graf et al. (2020) showed that
196 the number of articles including a DAS increase with the mandate of a DAS from the journal. We
197 recommend for journals, such as AI in Geo., who do not currently have a DAS mandate, to make
198 such a policy a priority. We encourage editors and peer reviewers to examine any DaCo repositories
199 provided to ensure that direct links are given to DaCo and sufficient metadata and documentation is
200 given with the DaCo. We support journals exploring a system which would remind corresponding
201 authors to periodically check for broken links within their articles and give a simple means to
202 update such links. In a rapidly changing environment where AI is increasingly being leveraged

203 in the sciences, it is imperative for journals to evolve their practices to ensure transparency and
204 accessibility. Adapting to these advancements will not only uphold scientific integrity but also
205 set a new standard for future research publications. Finally, we recommend that journals provide
206 authors with a clear set of guidelines for which justifications, if any, are acceptable and furthermore
207 mandate that the justification is given within their DAS.

208 *Acknowledgments.* This material is based upon work supported by the National Science Founda-
209 tion under Grant No. RISE-2019758. This work began as a class project for the course “Developing
210 Ethical and Responsible AI for the Earth Sciences” taught by A.M. at the University of Oklahoma,
211 thus support for the project also comes from the University of Oklahoma.

212 *Data availability statement.* The information collected on data availability statements and the
213 code utilized for Figs. 1-2 can be found at: <https://doi.org/10.5281/zenodo.13844985>.
214 The word cloud for Fig. 3 is generated by <https://www.jasondavies.com/wordcloud/>.

215 **References**

216 Bertram, M. G., J. Sundin, D. G. Roche, A. Sánchez-Tójar, E. S. J. Thoré, and T. Brodin, 2023:
217 Open science. *Current Biology*, **33** (15), R792–R797, <https://doi.org/10.1016/j.cub.2023.05.036>.

218 Briney, K. A., 2024: Measuring data rot: An analysis of the continued availability of shared data
219 from a Single University. *PLOS ONE*, **19** (6), e0304781, <https://doi.org/10.1371/journal.pone.0304781>.
220

221 Campbell, A., and J. Mu, 2023: Navigating Trust in Academic Research: The Rise of Data
222 Availability Statements – Part I. *Digital Science*.

223 Edwards, P. N., M. S. Mayernik, A. L. Batcheller, G. C. Bowker, and C. L. Borgman, 2011:
224 Science friction: data, metadata, and collaboration. *Social Studies of Science*, **41** (5), 667–690,
225 <https://doi.org/10.1177/0306312711413314>.

226 Fecher, B., and S. Friesike, 2014: Open Science: One Term, Five Schools of Thought.
227 *Opening Science: The Evolving Guide on How the Internet is Changing Research, Col-
228 laboration and Scholarly Publishing*, S. Bartling, and S. Friesike, Eds., Springer Interna-
229 tional Publishing, Cham, 17–47, https://doi.org/10.1007/978-3-319-00026-8_2, URL https://doi.org/10.1007/978-3-319-00026-8_2.
230

231 Goodman, A., and Coauthors, 2014: Ten Simple Rules for the Care and Feeding of Scientific Data.
232 *PLOS Computational Biology*, **10** (4), e1003542, <https://doi.org/10.1371/journal.pcbi.1003542>.

233 Graf, C., D. Flanagan, L. Wylie, and D. Silver, 2020: The Open Data Challenge: An Analysis of
234 124,000 Data Availability Statements and an Ironic Lesson about Data Management Plans. *Data*
235 *Intelligence*, **2** (4), 554–568, https://doi.org/10.1162/dint_a_00061.

236 Grant, R., and I. Hrynaszkiewicz, 2018: The Impact on Authors and Editors of Introducing Data
237 Availability Statements at Nature Journals. *International Journal of Digital Curation*, **13** (1),
238 195–203, <https://doi.org/10.2218/ijdc.v13i1.614>.

239 Haupt, S. E., and Coauthors, 2022: The History and Practice of AI in the Environmental Sciences.
240 *Bulletin of the American Meteorological Society*, **103** (5), E1351–E1370, [https://doi.org/10.](https://doi.org/10.1175/BAMS-D-20-0234.1)
241 [1175/BAMS-D-20-0234.1](https://doi.org/10.1175/BAMS-D-20-0234.1).

242 Liesenfeld, A., and M. Dingemane, 2024: Rethinking open source generative AI: open-washing
243 and the EU AI Act. *Proceedings of the 2024 ACM Conference on Fairness, Accountability, and*
244 *Transparency*, Association for Computing Machinery, New York, NY, USA, 1774–1787, FAccT
245 '24, <https://doi.org/10.1145/3630106.3659005>, URL <https://doi.org/10.1145/3630106.3659005>.

246 Maslej, N., and Coauthors, 2024: The AI Index 2024 Annual Report. Tech. rep., AI Index Steering
247 Committee, Institute for Human-Centered AI, Stanford University, Stanford, CA, 502 pp. URL
248 <https://aiindex.stanford.edu/report/>.

249 McGovern, A., A. Bostrom, M. McGraw, R. J. Chase, D. J. Gagne, I. Ebert-Uphoff, K. D.
250 Musgrave, and A. Schumacher, 2024: Identifying and Categorizing Bias in AI/ML for Earth
251 Sciences. *Bulletin of the American Meteorological Society*, **105** (3), E567–E583, [https://doi.org/](https://doi.org/10.1175/BAMS-D-23-0196.1)
252 [10.1175/BAMS-D-23-0196.1](https://doi.org/10.1175/BAMS-D-23-0196.1).

253 McGuinness, L. A., and A. L. Sheppard, 2021: A descriptive analysis of the data availability state-
254 ments accompanying medRxiv preprints and a comparison with their published counterparts.
255 *PLoS ONE*, **16** (5), e0250887, <https://doi.org/10.1371/journal.pone.0250887>.

256 Pineau, J., P. Vincent-Lamarre, K. Sinha, V. Lariviere, A. Beygelzimer, F. d'Alche Buc, E. Fox, and
257 H. Larochelle, 2021: Improving Reproducibility in Machine Learning Research(A Report from
258 the NeurIPS 2019 Reproducibility Program). *Journal of Machine Learning Research*, **22** (164),
259 1–20.

- 260 Schuster, D., M. Mayernik, and G. Mullendore, 2023: Products developed through the "What About
261 Model Data?, Determining Best Practices for Preservation and Replicability, EarthCube Research
262 Coordination Network" project. UCAR/NCAR - GDEX, URL [https://gdex.ucar.edu/dataset/id/
263 6962fde0-9f65-4530-9320-76c42866c821.html](https://gdex.ucar.edu/dataset/id/6962fde0-9f65-4530-9320-76c42866c821.html), <https://doi.org/10.5065/G936-Q118>.
- 264 Stall, S., and Coauthors, 2023: Ethical and Responsible Use of AI/ML in the Earth,
265 Space, and Environmental Sciences. URL [https://essopenarchive.org/users/536571/articles/
266 635008-ethical-and-responsible-use-of-ai-ml-in-the-earth-space-and-environmental-sciences](https://essopenarchive.org/users/536571/articles/635008-ethical-and-responsible-use-of-ai-ml-in-the-earth-space-and-environmental-sciences),
267 <https://doi.org/https://doi.org/10.22541/essoar.168132856.66485758/v1>.
- 268 Tedersoo, L., and Coauthors, 2021: Data sharing practices and data availability upon re-
269 quest differ across scientific disciplines. *Scientific Data*, **8** (1), 192, [https://doi.org/10.1038/
270 s41597-021-00981-0](https://doi.org/10.1038/s41597-021-00981-0).
- 271 UNESCO, 2021: UNESCO Recommendation on Open Science. Tech. rep., UN-
272 ESCO. <https://doi.org/10.54677/MNMH8546>, URL [https://unesdoc.unesco.org/ark:/48223/
273 pf0000379949](https://unesdoc.unesco.org/ark:/48223/pf0000379949).
- 274 Wilkinson, M. D., and Coauthors, 2016: The FAIR Guiding Principles for scientific data manage-
275 ment and stewardship. *Scientific Data*, **3** (1), 160 018, <https://doi.org/10.1038/sdata.2016.18>.
- 276 Wirz, C. D., and Coauthors, 2024: Increasing the Reproducibility and Replicability of Supervised
277 AI/ML in the Earth Systems Science by Leveraging Social Science Methods. *Earth and Space
278 Science*, **11** (7), e2023EA003 364, <https://doi.org/10.1029/2023EA003364>.