Reproducible Research and GIScience: an evaluation using GIScience conference papers

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Abstract

GIScience conference authors and researchers face the same computational reproducibility challenges as authors and researchers from other disciplines who use computers to analyse data. Here, to assess the reproducibility of GIScience research, we apply a rubric for assessing the reproducibility of 75 conference papers published at the GIScience conference series in the years 2012-2018. The rubric and process were previously applied to the publications of the AGILE conference series. The results of the GIScience paper assessment are in line with previous findings: descriptions of workflows and the inclusion of the data and software suffice to explain the presented work, but they do not enable the findings to be reproduced by a third party with reasonable effort. We summarise and adapt previous recommendations for improving this dire situation and invite the GIScience community to start a broad discussion on the reusability, quality, and openness of its research. The code and data for this article are published at `https://doi.org/10.5281/zenodo.4032875`.

2012 ACM Subject Classification Information systems~Geographic information systems

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Supplement Material The raw data for this work are the full texts of GIScience conference proceedings from the years 2012 to 2018 [30, 7, 19, 29]. The paper assessment results and source code of figures are published at https://github.com/nuest/reproducible-research-at-giscience and archived on Zenodo [24]. The used computing environment is containerised with Docker and Binder-ready using R 3.6.0 and Python 3.5.3. The R packages are installed from the MRAN snapshot of July 5th 2019, and Python packages are pinned to specific versions, see `requirements.txt` file.

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1 Introduction

A large proportion of GIScience research today uses software to analyse data on computers. This means that many articles published in the context of the GIScience conference series[1] fall into the categories of data science or computational research. Thereby, these articles face challenges of transparency and reproducibility in the sense of the Claerbout/Donoho/Peng terminology [2], where *reproduction* means a recreation of the same results using the same input data and workflow as the original authors. In previous work [23] we assessed the reproducibility of a selection of full and short papers from the AGILE conference series[2], a community conference organised by member labs of the Association of Geographic Information Laboratories in Europe (AGILE). The AGILE conference is closely related to GIScience conference in terms of scientific domain and contributing authors. Using systematic analysis based on a rubric for reproducible research, we found that the majority of AGILE papers neither provided sufficient information for a reviewer to evaluate the code and data and attempt a reproduction, nor enough material for readers to reuse or extend data or code from the analytical workflows. This is corroborated by research in related disciplines such as quantitative geography [3], qualitative GIS [20], geoscience [15], and e-Science [10]. The problems identified in these related research areas are directly transferable to GIScience, which operates at the intersections of aforementioned fields [11]. In any case, observations on the lack of reproducibility in all scientific fields contrast with the clear advantages and benefits of open and reproducible research both for individuals and for academia as a whole (cf. for example [6, 18, 17, 5]). As a consequence, we have initiated a process to support authors in increasing reproducibility for AGILE publications; as a main outcome, this initiative has produced author guidelines as well as strategies for the AGILE conference series[3].

An obvious question is whether the GIScience conference series faces the same issues and whether similar strategies could work for improvement. To begin this investigation, we conducted a simple text analysis of GIScience conference proceedings[4] to evaluate the relevance of computational methods in the conference papers. The analysis searched for several word stems related to reproducibility: generic words, e.g., "data", "software", or "process"; specific platforms, e.g., "GitHub"; and concrete terms, e.g., words starting with "reproduc" or "replic". Table 1 shows the results of the search for each year analysed. The take-away message from the text analysis is that algorithms, processing, and data play a large role in GIScience publications, but few papers mentioned code repositories or reproduction materials. Therefore, a more detailed manual assessment of the reproducibility of these

[1] `https://www.giscience.org/`

[2] `https://agile-online.org/conference`

[3] See the initiative website at `https://reproducible-agile.github.io/`, the author guidelines at `https://doi.org/10.17605/OSF.IO/CB7Z8` [21] and the main OSF project with all materials `https://osf.io/phmce/` [22].

[4] The full text analysis and the results is available in this paper's repository in the following files: `giscience-historic-text-analysis.Rmd` contains the analysis code; the result data are two tables with counts for occurences of words respectively word stems per year in `results/text_analysis_topwordstems.csv` and `results/text_analysis_keywordstems.csv`; a wordcloud per year is in file `results/text_analysis_wordstemclouds.png`.

Table 1 Reproducibility-related word stems in the corpus per year of proceedings

year	words	reproduc..	replic..	repeatab..	code	software	algorithm(s)	(pre)process..	data.*	result(s)	repository/ies	github/lab
2002	23782	6	2	0	11	61	191	150	897	129	62	0
2004	26728	4	1	0	34	50	138	258	849	263	4	0
2006	32758	6	0	0	12	32	335	250	856	164	0	0
2008	27356	3	6	1	3	11	331	146	854	218	17	0
2010	23004	3	1	0	8	16	164	276	650	162	0	0
2012	28860	2	0	0	101	27	238	190	1048	311	3	0
2014	29534	3	4	1	12	18	255	159	1070	228	3	0
2016	24838	2	0	0	23	21	333	150	1007	202	4	1
2018	23318	3	10	0	15	15	201	160	891	294	6	6
Total	240178	32	24	2	219	251	2186	1739	8122	1971	99	7

Note:
The very high value for 'code' in 2012 is due to a single paper about land use, for which different "land use codes" are defined, discussed and used.

publications was necessary.

The main contribution of this work addresses two objectives: First, it aims to investigate the state of reproducibility in the GIScience conference community. This investigation broadens our knowledge base about reproducibility in GIScience in general and teaches us more about the situation in the GIScience conference series specifically. Second, it aims to apply the assessment procedure used for AGILE conference papers (presented in the section Reproducibility assessment method) to the papers of the GIScience conference, so that the broader suitability of this procedure is evaluated using a different dataset. Such a transfer validates the developed methodology. Together, these objectives yield important findings for the discussion of reproducibility within the GIScience conference community and the GIScience discipline at large. Only then can a fruitful dialogue take place on whether and how to improve reproducibility for the GIScience conference series, and whether the recent steps taken at AGILE[5] could be an inspiration for GIScience conferences as well. We discuss these findings and present our conclusions in the final two sections (Discussion; Conclusions and outlook).

2 Related work

This work transfers a previously used method to a new dataset, whereby the original article [23] already provides an overview of reproducible research in general, including definitions, challenges, and shortcomings. In the following, we focus on recently published works and briefly introduce related meta-studies.

Few groups have attempted practical reproduction of computational works related to GIScience. Konkol et al. [16] conducted an in-depth examination of the computational reproducibility of 41 geoscience papers with a focus on differences between the recreated figures. The set of papers was, similar to our work, drawn from a fixed group of two outlets (journals), but it was further limited to recent papers providing code in the R language. Konkol et al. [16] also conducted actual reproductions, which we did not do here; yet, applying the same prerequisites to our dataset would be possible as a next step. One could attempt to reproduce the papers whose assessment points to a possible reproduction (i.e., level two or higher, see below). In a report on the reproducibility review at the AGILE conference 2020[6], the reproducibility committee summarised the process and documented relevant obstacles to reproducibility of accepted papers. The main issues identified in their report and by Konkol et al. [16] are quite coincident.

[5] See the initiative website at `https://reproducible-agile.github.io/`, the author guidelines at `https://doi.org/10.17605/OSF.IO/CB7Z8` [21] and the main OSF project with all materials `https://osf.io/phmce/` [22].
[6] `https://osf.io/7rjpe/`

Within the geospatial domain, Kedron et al. [12] provide a recent review of opportunities and challenges for reproducibility and replicability. They transfer solutions from other domains but also discuss and conceptualize the specific nature of a reproducibility and replicability framework when working with geospatial data, e.g., handling context, uncertainty of spatial processes, or how to accommodate the inherent natural variability of geospatial systems. In a similar manner, Brunsdon and Comber [4] investigate reproducibility within spatial data science, with special attention to big spatial data. They support the need for open tools, knowledge about code, and reproducibility editors at domain journals and conferences, but they also introduce the perspective that spatial analysis is no longer conducted only by GI/geo-scientists or geographers and connect reproducibility with critical spatial understanding. The conceptual work in these articles complements the assessment of reproducibility conducted in this paper.

Two recent studies from distant disciplines, wildlife science [1] and hydrology [27], relate to our work in this paper. Both investigate a random set of articles from selected journals and use a stepwise process of questions to determine the availability of materials, and eventually reproduce workflows if possible. Archimiller et al. [1] use a final ranking of 1 to 5 to specify the degree to which a study's conclusions were eventually reproduced. Similar to our classification scheme, their ranking models borrow the general notion of a *"reproducibility spectrum"* [25].

3 Reproducibility assessment method

3.1 Criteria

The assessment criteria used for the current study were originally defined in previous work, so we provide a short introduction here and refer to Nüst et al. [23] for details. The three assessment criteria are *Input Data*, *Methods*, and *Results*. *Input Data* comprises all datasets that the computational analysis uses. *Methods* encompasses the entire computational analysis that generates the results. Since *Methods* is difficult to evaluate as a whole, we split this criterion into three subcategories: *Preprocessing* includes the steps to prepare the *Input Data* before the main analysis; *Methods, Analysis, Processing* is the actual analysis; *Computational Environment* addresses the description of hard- and software. Finally, the criterion *Results* refers to the output of analysis, for example, figures, tables, and numbers.

For each of these (sub)categories, we assigned one of four levels unless the criterion was not applicable, *(Level NA)*. *(Level 0) Unavailable* means that it was not possible to access the paper's data, methods, or results, and that it was impossible to recreate them based on the description in the paper. *(Level 1) Documented* indicates that the paper still did not provide direct access to datasets, methods, or results, but that there was sufficient description or metadata to recreate them closely enough for an evaluation; yet, often a recreation was unlikely due to the huge amount of effort needed. With regard to the methods criteria, *Level 1* means that pseudo code or a textual workflow description was available. *(Level 2) Available* was assigned if the paper provided direct access to the materials (e.g., through a link to a personal or institutional website), but not in the form of an open and permanent identifier, such as a DOI. The indication of a DOI does not apply to the methods criteria, as it is not yet common practice to make a permanent reference to code, libraries and system environments with a single identifier. The gold standard, *(Level 3) Available and open*, requires open and permanent access to the materials (e.g., through public online repositories) and open licenses to allow use and extension.

Note that levels are ordinal numbers that can be compared (3 is higher than 2), but absolute differences between numbers must not be interpreted as equals. Moving one level up from 0 to 1 is not the same as from 1 to 2. While reaching 1 is fairly straightforward, jumping to level 2 means one must have an almost fully reproducible paper.

3.2 Process

The overall approach to assessing the reproducibility of GIScience papers, again, followed the previous assessment of AGILE papers [23]. The assessment was conducted by the same persons. All full papers in the GIScience conference series (from the 2012 to 2018 editions) were assessed. This is partly because of no obvious subset, such as the nominees for best papers as in the case of the AGILE conference series; this was also partly because we aimed to work with a larger dataset for potentially more informative results. Each GIScience paper was randomly assigned to two assessors who evaluated it qualitatively according to the five reproducibility criteria. The assessors were free in the way they approached the assigned evaluations. The particular process depended on the structure of the paper and the assessor's familiarity with the topic, and it could range from a quick browse to identify relevant statements to a thorough reading of the full text. The identification of relevant content could be supported to some extent by a PDF reader with multiple highlights, using keywords like e.g., "data, software, code, download, contribution, script, workflow". The results of the individual assessments were joined in a collaborative Google Spreadsheet. This spreadsheet also had a comments column for assessors to record relevant sources and decisions. When there was disagreement between assessors, arguments for and against a certain reproducibility level were discussed in the entire group of five assessors until a consensus was reached. Only then were the assessments merged into a single value, one year at a time. A snapshot of both the unmerged and merged values was stored as a CSV file in the collaboration repository for transparency and provenance[7]. Two independent assessors per paper increased the objectivity of the final assessment. Disagreements and conducting the assessment one year at a time, going backwards from the most recent year, were found helpful in aligning the interpretation of criteria and, in rare cases, led to an adjustment of similar cases in other papers.

The discussion about the correct assignment of levels made us reflect on how to apply the rubric for special situations. For the *Input Data* criterion, some papers had input data "available" at the time of writing/publication but it was not available at the time of evaluation, due to broken links, changes in the URL structure of a website, or projects and/or personal websites that were down or moved. In such cases, we gave the authors the benefit of the doubt and assumed the data were accessible some time after the publication of the conference proceedings. We did not give those papers an arbitrary score and discussed internally the best level per case; yet, such papers never earned a `3`, which would include permanent resolving of the link. Related to this criterion, simulation data, like the specification or configuration of agents in an agent-based system, was not treated as input data (*Level NA*), but as parameters of the main analysis, i.e., being part of the *Methods, Analysis, Processing*.

Preprocessing covers preparatory work for the actual analysis involving various tasks such as data selection, cleaning, aggregation and integration. However, the dividing line between

[7] The assessment results are in the file `results/paper_assessment.csv`. As an example, commit `464e630` and `2e8b1be` are the pre-merge and post-merge commit after completing the assessment of the papers from 2014. The pre-merge commit contains the assessments including the assessors' initials, e.g. "CG: 1, MK: 1".

data preprocessing and processing (i.e., the main analysis) is often thin and not always clearly defined. Several times, assessors' opinions were not in agreement if the preprocessing criterion was "not applicable" or "applicable"; if it was applicable, there was disagreement on whether it was not reproducible at all or hardly reproducible (`0` or `1`, respectively). Therefore, we decided to apply the rubric only in cases where papers themselves specifically mentioned a preprocessing task independent of the actual analysis or method, e.g., when clearly stated in separate sub-sections of the paper.

Lastly, human subject tests and surveys were also a special case. Human-related research activities were rated as `1` in the methods/analysis/processing criterion if sufficiently documented; nonetheless, a sufficient documentation in these cases did not mean that original sources were available or could be exactly recreated.

3.3 Paper corpus

In total, 87 papers from the GIScience conferences in 2012, 2014, 2016, and 2018 were assessed. Table 4 shows the full results of the assessment. For details on assigned assessors, authors, etc., please check the reproducibility package [24]. 12 papers (14%) across all years were identified as conceptual papers[8] and were not included in the corpus. The number of conceptual papers in GIScience conferences was low over the analysed years (2012: 4; 2014: 5; 2016: 3), going down to zero in the last year's proceedings (2018). This might suggest the increasingly predominant and ubiquitous role of analytics datasets and computational workflows in the generation of the final published results in the field.

4 Reproducibility of GIScience conference papers

Table 2 shows aggregated values for the assessed reproducibility levels. For 24 papers, the *Preprocessing* criterion was not applicable. This large number can be explained because the boundary between the *Preprocessing* criterion and the *Methods, Analysis, Processing* criterion is not always clear and is therefore subject to the assessor's interpretation. This does not mean that the papers in which the *Preprocessing* criteron was missing are not reproducible at all. Simply, in these cases, either no preprocessing is required or has been integrated into the main analysis. Obviously, if data preprocessing is required but it is either not indicated in the paper or is not provided as an additional (computational) step or resource, the ability to reproduce the paper will be seriously limited.

If we look at the median values of the five criteria (Table 2), a typical GIScience paper scores `11101`. This score translates in practical terms into a paper that is sufficiently documented to claim that reproduction could be attempted within a short time frame after publication. While such a level of reproducibility is typically accepted by journals and conferences today, it does not guarantee actual reproducibility or even reproduction. If we had to reproduce such a paper, this would require considerable effort, namely technical skills, communication with authors, and time not only to both gather, recreate, and/or analyse all the necessary resources (data, code, etc.) but also to recreate the specific computational environment of the paper, if the latter were even possible, since this is generally not specified (note the value `0` in the fourth position in `11101`).

Figure 1 shows the distribution of the reproducibility levels for each criterion. None of the papers reached the highest level of reproducibility on any criterion. Only 12 papers

[8] See [23] for a definition of "conceptual".

Table 2 Statistics of reproducibility levels per criterion (rounded to one decimal place)

	input data	preproc.	method/analysis/proc.	comp. env.	results
Min.	0.0	0.0	0	0.0	0.0
Median	1.0	1.0	1	0.0	1.0
Mean	0.7	0.8	1	0.3	1.1
Max.	2.0	2.0	2	1.0	2.0
NA's	1.0	24.0	0	0.0	0.0

reached level 2 in the *Input Data* criterion, which was still the highest number of that level across all criteria. Similar to previous results [23], the number of papers with level 0 for *Input Data* was especially high (33, corresponding to 44%), which is a significant barrier to reproduction since input data is not only unavailable but also cannot be recreated from the information provided in the paper.

Preprocessing applied to 51 publications, and the levels reached were generally low (0 or 1), level 2 being almost residual. Of these, 37 papers reach level 1. This represents about half of the papers with level 1 in the *Analysis* criterion, suggesting that data processing was clearly identified in some papers. For the other half, it was not clear whether data preprocessing tasks existed at all, or whether these tasks part of the main analysis. When data preprocessing steps are required but not reported, this situation becomes much more problematic, as this makes it noticeably difficult to reproduce the results of a paper.

Methods and *Results* criteria show a pretty similar distribution (see Figure 1). Indeed, 65 publications had level 1 in both criteria, which represents 87% of the papers assessed. In this sense, most of the assessed papers fall below the minimum standard for reproduction as regards the methods and results criteria. All papers except one had a value of 1 for the results criterion, which shows that the peer review worked as expected for almost all articles. In other words, authors are concerned with making the results understandable to the reviewers, which is not always the case for the other criteria. More generally, this aspect raises the question of whether peer review should stop in the absence of minimal evidence of the input data, analysis, and computational environment used in a paper. Without an explicit justification (confidential data, privacy concerns, etc), should a paper with level 0 (or NA) for the input data criterion get accepted for a conference?

Finally, papers scored worse on the *Computational Environment* criterion. Overall, 54 (72%) publications were level 0, which means that no clues were provided in the paper about the computing environment, tools, or libraries used in the reported analysis. The *Computational Environment* criterion and the *Input Data* criterion accounted for a considerable number of 0 values, which clearly signals a serious impediment to reproduction.

5 Discussion

5.1 State of reproducibility in the GIScience conference series

Our first research objective was to assess the state of reproducibility in the GIScience conference series. A recurrent issue found in the analysis was the inability to access input data based on the information provided in the paper. Most of the links and pointers to datasets reported at the time of publication were either broken (e.g., non-existing resource, HTTP 404 error, invalid URL syntax) or not available anymore (URL works but redirects to a different generic page; specific resource from the paper no longer exists). In these cases, a level of 2 in the *Input Data* criterion was deserved at the time of publication; however, when evaluating the level of reproducibility some time later, as was done in this work, level

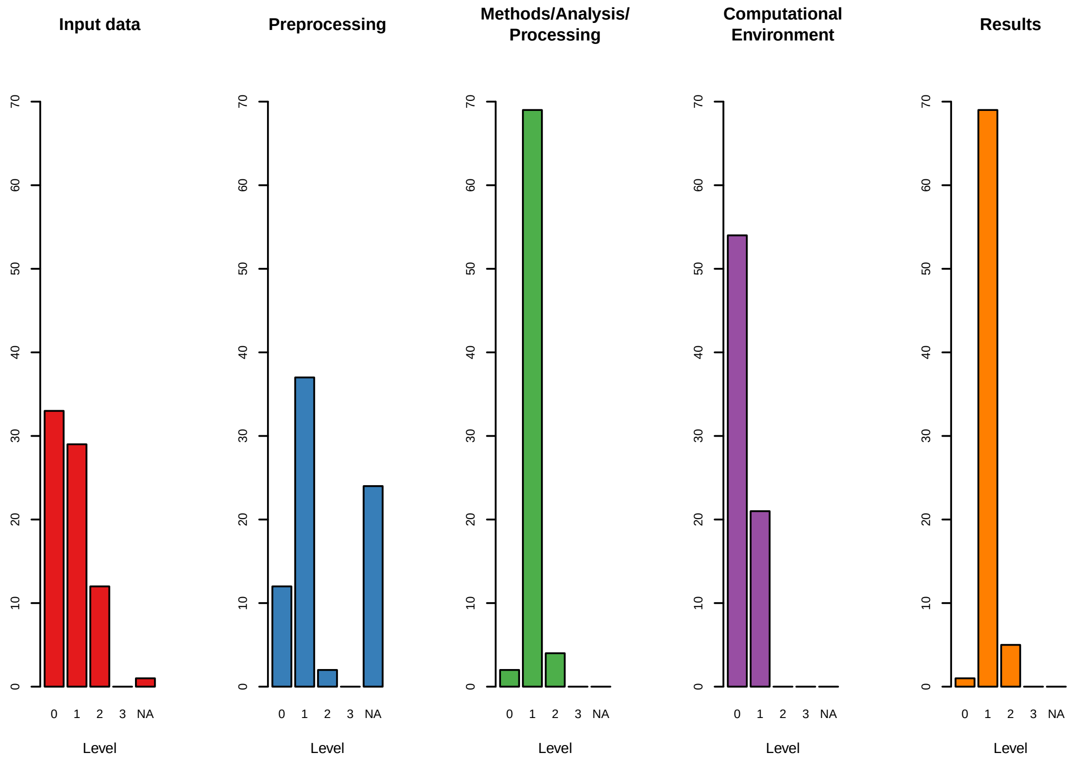

Figure 1 Barplots of reproducibility assessment results; levels range from 0 (leftmost bar) to 'not applicable' (rightmost bar).

2 is no longer suitable for those papers. From the reproducibility point of view, the input data was not accessible, even if contacting the authors could still be attempted. According to the meaning of the criterion and in practical terms, this is equivalent to including the statement "available upon request" in the paper and thereby level 0. An important part of reproducibility is that access to material should not degrade over time, which is best achieved by depositing data in repositories, including sensitive data (using the appropriate mechanisms), and properly citing it. In this assessment of reproducibility, we decided to give the authors the benefit of the doubt and awarded a value of 2 for *Input Data* even if we could not conclusively determine, e.g., by using the Internet Archive's Wayback Machine[9], whether the original website ever existed.

Regarding the common situation of a paper with "all 1s", our interpretation is that this is indeed a regular paper that is up to current scientific standards. Even if there is a value of 0 in some criteria, that does not mean the paper should not have passed peer review - after all, we specifically assessed a paper's reproducibility using criteria, which likely were not included at all in the call for papers or in the reviewer guidelines, and therefore did not receive much attention from authors or reviewers. Thus, we are analysing in the historical context of when there were no concrete incentives to push these aspects, beyond the general concerns for good scientific practice.

However, this overall picture matches the somewhat worrisome focus that researchers, editors, and publishers have on publishing exciting results in science, and not giving as much

[9] https://web.archive.org/.

care to publishing the full process and collection of parts that would allow readers to try to fully understand the research. Clearly, a level of `0` in *Input Data* is problematic, because without sufficient knowledge about the characteristics of the input data, all attempts at reproducing results are bound to fail, even when the textual documentation of the data would potentially allow for an expensive recreation of the computational workflow.

5.2 Transferability of method

Concerning our second research objective, we can state that the process and the rubric worked, but faced similar challenges as we recalled from its first application. The preprocessing criterion caused many discussions among the reproducibility reviewers during the assessment. It is often not clear or a matter of interpretation if a particular processing step belongs to a minor basic transformation of input data, if it is already part of the main analysis, and when it is a truly distinct step in the process. The borders are vague and hence scores should be interpreted with caution. Future assessments could provide a more precise definition for *pre*-processing, e.g., only use it if the authors use the term, or might consider to drop the category.

In a similar vein, the computational environment is difficult to clearly distinguish from analysis, and technology and practices for the effective management of the computing environment have reached mature states relatively recently. Future assessments could prepare concrete rules as reliefs for historic workflows, similar as discussed for input data above.

Furthermore, it is important to remember that the levels of reproducibility are not equidistant in the sense that a level of `2` would be twice as good as a level of `1`, or that the effort needed is twice as high. A level of 1 should be the standard for peer-reviewed papers. Moving it to `2` requires several steps and actions, while reaching the gold standard of `3` is a comparatively small step from level `2` - the main difference is to use public repositories with a DOI - but with a comparatively positive impact in permanent accessibility.

5.3 Comparison of conferences

Given that we followed the same process as in [23] and demonstrated the transferability of the method, comparing the two conference series seems appropriate. It is important to remember that we do not attempt such a comparison with the objective of declaring a "winner". The two conferences are similar enough, as shown below, for a comparison, yet they are too distinct and diverse in setup, process, and audience for such simplistic ranking. However, such comparison is required to sensibly discuss whether the guidelines developed for AGILE might also be promising for GIScience: Are they transferable? If not, what adaptations seem necessary?

Concerning the contributing and participating academic communities, Egenhofer et al. [8] and Kemp et al. [13] both include the conferences considered here as outlets for GIScience. Further, Keßler et al. [14] investigate the bibliographies of four GIScience conference series, including GIScience and AGILE. They list 15 authors who have published in all GIScience conference. We conducted a cursory investigation of the body of authors for full papers, revealing significant overlap[10]: Out of 571 unique AGILE and 405 unique GIScience full paper authors, 86 published in both conferences, and this includes all 15 authors mentioned by Keßler et al. [14]. Therefore, the strong relation between the AGILE and GIScience

[10] The data and code for the brief exploration into the authorships across the conferences considered in this work can be found in the directory `author_analysis` of this paper's reproducibility package [24].

Table 3 Mean values per criterion for both conferences (rounded to two decimal places)

Criterion	AGILE full papers	GIScience papers
input data	0.67	0.72
method/analysis/processing	1.00	1.03
computational environment	0.62	0.28
results	0.88	1.05

conference series provides the foundation for applying the same methodology to GIScience that has been developed for AGILE conference publications and will probably result in similar implications for improving reproducibility.

Concerning the paper corpora, the publication years considered here (2012-2018) are similar to the assessment of AGILE papers (2010-2017), which makes the results comparable in the sense of what methods and tools would have been available for authors. Furthermore, we note that both conferences have a similar ratio of conceptual papers which were not assessed for reproducibility: In the AGILE corpus we identified 5 of 32 conceptual papers (15.6%), in the GIScience corpus there were 12 of 87 (13.8%). This indicates that both conferences have similar share of papers that used, at least in part, computational methods. On the content of the papers, our overall impression was that a larger share of GIScience papers included theoretical, conceptual, or methodological aspects, while AGILE papers seemed to feature more empirical and/or applied geoinformation science research.

Regarding the results of the reproducibility assessments as summarised in Table 3, the nature of the data and sample size does not support statistical analyses on significant differences. Nevertheless, looking at the *Input Data* category, GIScience has a slightly higher mean value compared to AGILE full papers (0.72 as opposed to 0.67) and a median of 1. These values indicate that the GIScience contributions had a slightly better, but by no means optimal, availability of input data. The pattern of reproducibility of the papers' workflows (category *Method, Analysis, Processing*) was very similar for the two conference series: The overwhelming majority of papers achieved a level of `1`, resulting in a mean of 1.03 for GIScience and 1 for AGILE full papers. The *Computational Environment* category was not that different either: AGILE scored better with a mean of 0.62 vs. 0.28 for GIScience. The *Results* category scores were again slightly higher for GIScience, with a mean of 1.05 vs. a mean of 0.88 for AGILE. Several papers in AGILE received a level of `0` here, indicating that crucial information is missing to connect analysis outputs and presented results. We refrain from comparing the *Preprocessing* category, because our analysis has shown that this is a somewhat contentious dimension among assessors.

There are differences to consider between the two conference series. GIScience is a biannual conference series whereas AGILE is annual, and they feature different pre-publication review processes and review management systems: In AGILE both authors and reviewers are anonymous, while in GIScience only the reviewers are. Furthermore, the AGILE conference series has the AGILE association[11] as an institutional supporter, which means a more stable organizational and financial framework for activities spanning more than one or between conferences. However, like GIScience, local conference organizers for AGILE have the main financial burden and experiences are informally handed over between organizing committees. Geographic focus is also different: GIScience has a global target audience and the individual conferences are likely to be different in their contributor communities because

[11] `https://agile-online.org/`.

of the moving conference location, which often means lowered accessibility for other parts of the world. AGILE, by comparison, has a European focus, and, although the conference location moves every year, accessibility is less diverse. This likely translates into a less fluctuating and less geographically diverse audience at AGILE.

This comparison lets us draw two main conclusions. First, we conclude that both the target audience and the content of the two conference series are similar enough to be afflicted with similar shortcomings in terms of reproducibility, and, thus, they both likely respond to similar solutions. Second, we conclude that the AGILE conference series seems structurally better positioned to support changing habits, because of a more stable audience and institutional support. The introduction of the AGILE reproducibility guidelines was done within a short time frame and with financial support in the form of an "AGILE initiative", including travel funding for an in-person workshop. For GIScience, the task of changing the review process to foster better reproducibility falls squarely on the shoulders of the changing program committees. However, the initial results of AGILE's new guidelines show that even small changes can lead to a significantly improved outcome.

6 Conclusions and outlook

In this work we investigated the reproducibility of several years of GIScience conference publications. The paper corpus is large enough for a representative sample. The corpus size is comparable to that used for the AGILE assessment study. The corpora have different but largely overlapping time windows. It was never the intention of this study to rate the papers or to compare AGILE vs. GIScience conference quality. We also do not question that the research presented in these papers is sound and relevant, since they were accepted for publication at a reputable conference. Instead, we investigated the papers along a single desirable quality dimension, reproducibility, which implies requirements on openness and transparency.

Using a similarly high bar for reproducibility as in the earlier assessment study, the results clearly show a lot of room for improvement, as none of the presented articles were readily reproducible. The majority of articles provided some information, but not to the degree required to facilitate transparent, and, most relevantly, reusable research based on data and software. Overall, this is very similar to the outcomes of our earlier study on AGILE papers. As part of the AGILE assessment, we described concrete recommendations for individuals and organizations to improve paper reproducibility [23]. We have argued that AGILE and GIScience share a sufficiently common starting position, domain/discipline characteristics, audience, and author community, such that for both communities the strategies to improve the situation should be similar. Therefore, the previously identified recommendations are directly transferable to the GIScience conference series, the most important recommendations being (1) promoting outstanding reproducible work, e.g., with awards or badges, (2) recognizing researchers' efforts to achieve reproducibility, e.g., with a special track for reproducible papers, implementing a reproducibility reviewer, open educational resources, and helpful author guidelines including data and software citation requirements and a specific data/software repository, and (3) making an institutional commitment to a policy shift that goes beyond mere accessibility [28]. These changes require a roadmap and a clear year, say 2024, when GIScience starts to only accept computationally reproducible submissions and to check reproducibility before papers are accepted. The concluding statement of Archmiller et al. [1] is directly transferable to GIScience: The challenges are not insurmountable, and increased reproducibility will ensure scientific integrity.

The AGILE reproducible paper guidelines [21] and the associated reproducibility review processes as well as other community code review systems such as CODECHECK [9] are open and "ready to use". They can also be adopted for GIScience conferences, e.g., to suit the peer review process goals and scheduling. Kedron et al. [12] stressed the need for a comprehensive balanced approach to technical, conceptual, and practical issues. They further pointed out that availability must not lead to adoption. Therefore, a broad discourse around these recommendations, tools, and concepts would be beneficial for all members of the community, whether their work is more towards conceptual, computational, or applied GIScience. A survey for authors, as conducted for AGILE [23], could help identify special requirements and specific circumstances, beyond the findings presented here and in related work.

Future work may transfer the assessment process to other major events and outlets for GIScience research, such as GeoComputation or COSIT conferences and domain journals (cf. [8] for an extensive list), but we would not expect significantly differing results. Practical reproductions of papers and even replications of fundamental works are even more promising projects to convincingly underpin a call for a culture change. For example, Egenhofer et al. [8] provide for a list of the most frequently cited articles as potential candidates. Such a project would ideally be supported with proper funding. If the observed trend of non-reproducibility is continued in further, or in the case of replications, much more detailed evaluations, which we fear it might, the GIScience community should take action and improve its state of reproducibility. A timely adoption of the technological and procedural solutions may allow GIScience researchers, together with the entirety of academia, to level up and approach the challenges of the *"second phase of reproducible research"* by tackling long-term funding for maintenance of code and data and building supporting infrastructure for reproducible research [26].

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A Appendix

Table 4 Assessment results excerpt; for all fields (including assessors, authors, and assessment comments) see reproducibility package at `https://doi.org/10.5281/zenodo.4032875`.

year	title	conceptual	input data	preproc.	method/ anal./ proc.	comp. env.	results
2018	Early Detection of Herding Behaviour during Emergency Evacuations	FALSE	1	NA	1	0	1
2018	What Makes Spatial Data Big? A Discussion on How to Partition Spatial Data	FALSE	0	1	1	0	1
2018	Intersections of Our World	FALSE	0	1	1	0	1
2018	Considerations of Graphical Proximity and Geographical Nearness	FALSE	0	NA	1	0	1
2018	An Empirical Study on the Names of Points of Interest and Their Changes with Geographic Distance	FALSE	0	1	1	0	1
2018	Outlier Detection and Comparison of Origin-Destination Flows Using Data Depth	FALSE	0	0	0	0	1
2018	Is Salience Robust? A Heterogeneity Analysis of Survey Ratings	FALSE	1	1	1	0	1
2018	Labeling Points of Interest in Dynamic Maps using Disk Labels	FALSE	1	2	2	0	1
2018	Improving Discovery of Open Civic Data	FALSE	0	NA	1	0	1
2018	Local Co-location Pattern Detection: A Summary of Results	FALSE	0	1	1	1	1
2018	Detection and Localization of Traffic Signals with GPS Floating Car Data and Random Forest	FALSE	0	1	1	1	1
2018	Heterogeneous Skeleton for Summarizing Continuously Distributed Demand in a Region	FALSE	0	NA	1	0	1
2018	A Network Flow Model for the Analysis of Green Spaces in Urban Areas	FALSE	1	1	1	1	1
2018	Continuous Obstructed Detour Queries	FALSE	0	0	1	1	1
2018	Enhanced Multi Criteria Decision Analysis for Planning Power Transmission Lines	FALSE	0	1	1	1	1
2018	FUTURES-AMR: Towards an Adaptive Mesh Refinement Framework for Geosimulations	FALSE	0	0	1	1	1
2018	xNet+SC: Classifying Places Based on Images by Incorporating Spatial Contexts	FALSE	0	1	1	1	1
2016	Computing River Floods Using Massive Terrain Data	FALSE	2	1	1	1	1
2016	Partitioning Polygons via Graph Augmentation	FALSE	0	NA	1	0	1
2016	Hierarchical Prism Trees for Scalable Time Geographic Analysis	FALSE	2	2	2	0	2
2016	Mining Network Hotspots with Holes: A Summary of Results	FALSE	1	0	1	0	1
2016	Distance-Constrained k Spatial Sub-Networks: A Summary of Results	FALSE	0	0	1	1	1
2016	GIScience Considerations in Spatial Social Networks	TRUE	NA	NA	NA	NA	NA
2016	On Distortion of Raster-Based Least-Cost Corridors	FALSE	0	0	1	0	1
2016	Model-Based Clustering of Social Vulnerability to Urban Extreme Heat Events	FALSE	1	1	1	0	1
2016	Representing the Spatial Extent of Places Based on Flickr Photos with a Representativeness-Weighted Kernel Density Estimation	FALSE	1	1	1	0	1
2016	Scaling Behavior of Human Mobility Distributions	FALSE	0	1	1	1	1
2016	pFUTURES: A Parallel Framework for Cellular Automaton Based Urban Growth Models	FALSE	0	0	1	1	1
2016	From Data Streams to Fields: Extending Stream Data Models with Field Data Types	TRUE	NA	NA	NA	NA	NA
2016	Point Partitions: A Qualitative Representation for Region-Based Spatial Scenes in R2	TRUE	NA	NA	NA	NA	NA
2016	Fine Scale Spatio-Temporal Modelling of Urban Air Pollution	FALSE	0	1	1	0	1
2016	Modeling Checkpoint-Based Movement with the Earth Movers Distance	FALSE	2	1	1	0	1
2016	Exploratory Chronotopic Data Analysis	FALSE	1	1	1	0	1
2016	Exploring the Notion of Spatial Lenses	FALSE	1	1	1	0	1
2016	Moon Landing or Safari? A Study of Systematic Errors and Their Causes in Geographic Linked Data	FALSE	1	0	1	0	1

Table 4 Assessment results excerpt; for all fields (including assessors, authors, and assessment comments) see reproducibility package at `https://doi.org/10.5281/zenodo.4032875`. *(continued)*

year	title	conceptual	input data	preproc.	method/ anal./ proc.	comp. env.	results
2016	Circles in the Water: Towards Island Group Labeling	FALSE	0	NA	1	0	1
2016	An Algorithmic Framework for Labeling Road Maps	FALSE	2	1	1	1	2
2016	Measuring Cognitive Load for Map Tasks Through Pupil Diameter	FALSE	1	1	1	1	1
2014	Map Schematization with Circular Arcs	FALSE	0	NA	1	0	1
2014	Travel-Time Maps: Linear Cartograms with Fixed Vertex Locations	FALSE	0	NA	1	0	1
2014	3D Network Spatialization: Does It Add Depth to 2D Representations of Semantic Proximity?	FALSE	1	1	1	1	1
2014	Uncertainty Analysis of Step-Selection Functions: The Effect of Model Parameters on Inferences about the Relationship between Animal Movement and the Environment	FALSE	2	1	1	0	1
2014	Logic Scoring of Preference and Spatial Multicriteria Evaluation for Urban Residential Land Use Analysis	FALSE	0	1	1	0	1
2014	Spatial Weights: Constructing Weight-Compatible Exchange Matrices from Proximity Matrices	FALSE	0	0	1	0	1
2014	Spatial Graphs Cost and Efficiency: Exploring Edges Competition by MCMC	FALSE	1	1	1	0	1
2014	Geosemantic Network-of-Interest Construction Social Media Data	FALSE	1	1	1	0	1
2014	Data Quality Assurance for Volunteered Geographic Information	FALSE	1	1	1	0	1
2014	Re-Envisioning Data Description Using Peirce Pragmatics	TRUE	NA	NA	NA	NA	NA
2014	Fields as a Generic Data Type for Big Spatial Data	FALSE	1	1	1	0	1
2014	Linked Data - A Paradigm Shift for Geographic Information Science	TRUE	NA	NA	NA	NA	NA
2014	An Ontology Design Pattern for Surface Water Features	TRUE	NA	NA	NA	NA	NA
2014	An Indoor Navigation Ontology for Production Assets in a Production Environment	FALSE	0	NA	0	0	1
2014	Wayfinding Decision Situations: A Conceptual Model and Evaluation	FALSE	1	1	1	0	1
2014	Understanding Information Requirements in Text Only Pedestrian Wayfinding Systems	FALSE	1	NA	1	0	1
2014	Automatic Itinerary Reconstruction from Texts	FALSE	1	1	1	0	2
2014	Integrating Sensing and Routing for Indoor Evacuation	FALSE	0	NA	1	0	1
2014	Significant Route Discovery: A Summary of Results	FALSE	2	0	1	0	1
2014	Location Oblivious Privacy Protection for Group Nearest Neighbor Queries	FALSE	2	NA	1	0	1
2014	Practical Approaches to Partially Guarding a Polyhedral Terrain	FALSE	1	NA	1	0	1
2014	Oriented Regions for Linearly Conceptualized Features	TRUE	NA	NA	NA	NA	NA
2014	RCC*-9 and CBM*	TRUE	NA	NA	NA	NA	NA
2012	Combining Trip and Task Planning: How to Get from A to Passport	TRUE	NA	NA	NA	NA	NA
2012	Automated Centerline Delineation to Enrich the National Hydrography Dataset	FALSE	2	1	1	1	1
2012	Evolution Strategies for Optimizing Rectangular Cartograms	FALSE	1	1	1	1	1
2012	Context-Aware Similarity of Trajectories	FALSE	2	1	1	0	1
2012	Generating Named Road Vector Data from Raster Maps	FALSE	1	NA	1	0	1
2012	An Ordering of Convex Topological Relations	TRUE	NA	NA	NA	NA	NA
2012	Toward Web Mapping with Vector Data	FALSE	0	NA	1	0	1
2012	spatial@linkedscience Exploring the Research Field of GIScience with Linked Data	FALSE	2	1	1	1	2
2012	Crowdsourcing Satellite Imagery Analysis: Study of Parallel and Iterative Models	FALSE	0	0	1	0	1

Table 4 Assessment results excerpt; for all fields (including assessors, authors, and assessment comments) see reproducibility package at `https://doi.org/10.5281/zenodo.4032875`. *(continued)*

year	title	conceptual	input data	pre-proc.	method/ anal./ proc.	comp. env.	results
2012	Quantifying Resolution Sensitivity of Spatial Autocorrelation: A Resolution Correlogram Approach	FALSE	0	1	1	1	1
2012	LocalAlert: Simulating Decentralized Ad-Hoc Collaboration in Emergency Situations	FALSE	NA	NA	2	1	1
2012	High-Level Event Detection in Spatially Distributed Time Series	FALSE	0	1	1	0	1
2012	Towards Vague Geographic Data Warehouses	FALSE	0	NA	2	0	2
2012	Measuring the Influence of Built Environment on Walking Behavior: An Accessibility Approach	FALSE	1	1	1	0	1
2012	Social Welfare to Assess the Global Legibility of a Generalized Map	FALSE	0	NA	1	0	1
2012	Investigations into the Cognitive Conceptualization and Similarity Assessment of Spatial Scenes	FALSE	1	NA	1	1	1
2012	A Qualitative Bigraph Model for Indoor Space	TRUE	NA	NA	NA	NA	NA
2012	Dynamic Refuse Collection Strategy Based on Adjacency Relationship between Euler Cycles	FALSE	2	NA	1	0	1
2012	Impact of Indoor Location Information Reliability on Users Trust of an Indoor Positioning System	FALSE	1	NA	1	0	1
2012	Ontology for the Engineering of Geospatial Systems	FALSE	1	NA	1	0	1
2012	Preserving Detail in a Combined Land Use Ontology	FALSE	1	1	1	0	0
2012	The Maptree: A Fine-Grained Formal Representation of Space	TRUE	NA	NA	NA	NA	NA
2012	Automatic Creation of Crosswalk for Geospatial Metadata Standard Interoperability	FALSE	1	0	1	0	1
2012	A Dartboard Network Cut Based Approach to Evacuation Route Planning: A Summary of Results	FALSE	2	NA	1	1	1
2012	Hybrid Geo-spatial Query Methods on the Semantic Web with a Spatially-Enhanced Index of DBpedia	FALSE	1	NA	1	0	1
2012	Extracting Dynamic Urban Mobility Patterns from Mobile Phone Data	FALSE	0	1	1	0	1