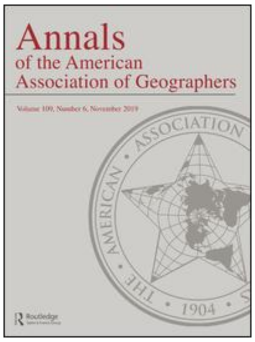

Annals of the American Association of Geographers

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/raag21

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To cite this article: Daniel Nüst & Edzer Pebesma (2020): Practical Reproducibility in Geography and Geosciences, Annals of the American Association of Geographers, DOI: 10.1080/24694452.2020.1806028

To link to this article: https://doi.org/10.1080/24694452.2020.1806028

Practical Reproducibility in Geography and Geosciences

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Reproducible research is often perceived as a technological challenge, but it is rooted in the challenge to improve scholarly communication in an age of digitization. When computers become involved and researchers want to allow other scientists to inspect, understand, evaluate, and build on their work, they need to create a research compendium that includes the code, data, computing environment, and script-based workflows used. Here, we present the state of the art for approaches to reach this degree of computational reproducibility, addressing literate programming and containerization while paying attention to working with geospatial data (digital maps, geographic information systems). We argue that all researchers working with computers should understand these technologies to control their computing environment, and we present the benefits of reproducible workflows in practice. Example research compendia illustrate the presented concepts and are the basis for challenges specific to geography and geosciences. Based on existing surveys and best practices from different scientific domains, we conclude that researchers today can overcome many barriers and achieve a very high degree of reproducibility. If the geography and geosciences communities adopt reproducibility and the underlying technologies in practice and in policies, they can transform the way researchers conduct and communicate their work toward increased transparency, understandability, openness, trust, productivity, and innovation. *Key Words: computational reproducibility, reproducible research, scholarly communication.*

Reproducible research is often perceived as primarily a technological challenge, but it is really rooted in the challenge to adjust scholarly communication to today's level of digitization and diversity of scientific outputs. Common academic challenges, such as broken metrics and pressure to publish articles over other products (see, e.g., Piwowar 2013; Nosek et al. 2015), have a negative impact on reproducibility. The state of reproducibility in geosciences and GIScience was investigated by Konkol, Kray, and Pfeiffer (2019) and Nüst, Boettiger, and Marwick (2018), respectively, and both studies show that it needs to improve. Other fields support this result; for example, Brunsdon (2016) on quantitative geography, Wainwright (2020) on an informal search in critical geography, Sui and Kedron (2020) on the conceptual challenges of reproducibility and replication in geography, and Sui and Shaw (2018) on the lack of knowledge about the state of reproducibility in human dynamics.

In this article, we present the current state of the art for practical reproducibility of research and connect it to geography and geosciences. The challenges around reproducible research manifest in the general lack of knowledge on how to work reproducibly and the small fraction of published reproducible articles. Interestingly, this is the case even though the individual and overall benefits of reproducibility (Vandewalle, Kovacevic, and Vetterli 2009; Donoho 2010; Markowetz 2015; Marwick 2015; Kray et al. 2019) and the innovative potential of working reproducibly, which include, for example, "unhelpful … non-reproducibility" (Sui and Kedron 2020), better collaboration (Singleton, Spielman, and Brunsdon 2016), and new pathways (Waters 2020), are increasingly known and common concerns are debunked (Barnes 2010). Editorial requirements and author guidelines are an effective means to encourage reproducibility, but they are not widespread enough or are still too lax (cf. Nosek et al. 2015; Singleton, Spielman, and Brunsdon 2016; Stodden, Seiler, and Ma 2018), so further incentives are needed for a change of habits and culture (Munafó et al. 2017; Nüst, Boettiger, and Marwick 2018). Because many solutions for practical reproducibility are not discipline specific, we include literature from other domains to corroborate the small body of work in "geo" fields, but we stick to examples and

Annals of the American Association of Geographers, 0(0) 2020, pp. 1–11
Initial submission, November 2019; revised submission, March 2020; final acceptance, April 2020
Published by Taylor & Francis, LLC.

highlight particular concerns for these communities of practice. For a much more extensive and comprehensive overview of the topic, we refer the reader to the recent consensus study report *Reproducibility and Replicability in Science* (National Academies of Sciences, Engineering, and Medicine 2019).

We follow the Claerbout/Donoho/Peng terminology (Barba 2018) and distinguish reproduction from replication[1] and reproducibility to mean *computational reproducibility* (National Academies of Sciences, Engineering, and Medicine 2019). Replicability is "the ultimate standard" (Peng 2011), because it requires independent confirmation and potentially yields new findings. Yet replication poses fewer technological challenges: Hypotheses, results, and conclusions are communicated with text and are addressed by some form of peer review. A suitable methodology for independent repetition can be developed from the text. Replication demands, however, that a particular study can be replicated; that is, that data sets used can be re-collected or computations can be repeated (Peng 2011). In studies describing particular areas and time periods of the Earth, this might not be possible; for instance, satellite images or interviews can only be taken once, at a particular moment in time, by a particular instrument or person, respectively. Furthermore, large-scale computations could be prohibitively expensive to replicate (Šimko et al. 2019), specialized hardware can be singular (Santana-Perez and Pérez-Hernández 2015), and real-time data streams would have to be openly recorded constantly (cf. Brunsdon 2016).

When studies are impossible to replicate for conceptual or practical reasons, reproducibility is the only way we can ensure that a scientific claim can be evaluated, and it becomes a minimal standard (Peng 2011; Sandve et al. 2013). Open data alone do not sufficiently guarantee reproducibility despite great advancements driven by the FAIR principles and research data management (see Wilkinson et al. 2016; Higman, Bangert, and Jones 2019), but workflows and processes must be open, too (Chen et al. 2019). The dynamic nature of the development processes makes it particularly important that concerns around computational reproducibility—that is, all aspects of computers involved in research—are comprehensively considered from the start. Otherwise, science falls short of communicating results effectively, as stated in Claerbout and Karrenbach's claim: "An article about a computational result is advertising, not scholarship. The actual knowledge is the full software environment, code and data, that produced the result" (adapted from Donoho [2010], who paraphrased Claerbout and Karrenbach 1992).

So, science today is too complicated for brief articles to fully communicate knowledge (Donoho 2010; Marwick 2015), and "[…] paradoxically, these in-silico experiments are often more difficult to reproduce than traditional laboratory techniques" (Howe 2012, 36). Peng (2011) introduced a *spectrum of reproducibility*, which is useful to inclusively acknowledge limitations and identify the current state of individual pieces of work and practices. Peng (2011) further argued that researchers should not wait for a comprehensive solution and concluded, "developing a culture of reproducibility … will require time and sustained effort" (1227). As part of this effort, we present the following tools and discuss challenges for reaching a high degree of computational reproducibility, fully communicating knowledge, and making in silico experiments reproducible when using and presenting geospatial data.

Reproducible Workflows in Geography and Geosciences

Creating Reproducible Workflows

Scientists must realize how fragile the typical research workflows are today. We have grown accustomed to the experience that a computer-based analysis we conduct today still works tomorrow; yet, although this is often the case, when there are differences, they can be very hard to explain, despite their dramatic effect (as documented, e.g., in Gronenschild et al. 2012; Bhandari Neupane et al. 2019). The lack of reported failures from geography and geosciences is not reassuring, and measures to improve reproducibility have been suggested. For example, Gil et al. (2016) presented the *Geoscience Paper of the Future* based on a thorough analysis of developments and challenges, and they give useful and concrete steps for modern digital open scholarship; Singleton, Spielman, and Brunsdon (2016) described a framework for reproducible publications based on Open GIS, open data, and workflow models for an Open Geographic Information science (Open GISc) going beyond text-centric publications. Building on these ideas, we present a practical approach for reproducible workflows and extend previous work with a deliberate management of the computing environment.

A *computing environment* is the totality of hardware and software components involved in a particular workflow. The description of the computing environment must be understandable by both machines and humans: by machines so that snapshots can be taken, the environment can be moved, or infrastructure can provision required capabilities (e.g., using ontologies; Santana-Perez and Pérez-Hernández 2015); by humans so that failures can be investigated and fixed. This documentation can be crafted manually, generated with the assistance of tools (e.g., Jupyter Project et al. 2018; Nüst and Hinz 2019), or recorded as provenance; for example, using scientific workflow management systems (see National Academies of Sciences, Engineering, and Medicine [2019], for details, which are beyond the scope of this work). A well-defined computing environment increases trust in the stability of results and the chances that third parties can also execute an analysis. Hirst (2019) coined three components of a computing environment: *physical*, *logical*, and *cultural*. The Examples and Conclusions sections cover the cultural component.

The physical component is the hardware; for example, the researcher's laptop, a university's high-performance computing facility, a Global Positioning System device, sensors, or instruments. Such devices might be preserved physically and investigated if problems arise but at very high costs (e.g., regular testing and replacement of parts). These costs are probably too high for regular research, and, at this stage of reproducibility, physical components are too rarely the source of critical issues. Thus, this component must be documented in detail (e.g., product names, IDs, manufacturing batches) and, where self-built, have open construction plans. It is worth noting here that quite often software has a much longer life span than hardware, and outdated hardware can often, although much later, be emulated by software.

To capture the logical component, common software development methods, such as using a language's package manager and repository[2] and practicing version pinning in the respective configuration files, allow freezing the logical component in a specific state. Virtualization (Howe 2012) and containerization[3] (Boettiger 2015) provide adequate solutions to capture full software stacks; that is, both programs' researchers are aware of obvious and unobvious dependencies (Perkel 2019). Containers can be created from a recipe file, which provides an additional layer of transparency and safeguarding (Nüst and Hinz 2019) independent of the specific container implementation (Santana-Perez and Pérez-Hernández 2015), or even automatically in a deterministic way (Jupyter Project et al. 2018). Container preservation is actively researched (Rechert et al. 2017; Emsley and De Roure 2018). Such configuration files and recipes can be managed using a version control system for retracing errors and auditing (Ram 2013). The application of Docker,[4] Singularity,[5] or supportive automating tools (Jupyter Project et al. 2018) is a core skill for geoscientists and geographers analyzing or visualizing data with computers.

The goal of describing the computing environment is to allow others to re-create, scrutinize, or extend it. This becomes more difficult when (1) the logical component is directly linked with the physical component; for example, bespoke optimized software for a particular computing, infrastructure, such as high-performance computing; or (2) critical parts of the computations involve proprietary software.[6]

A *script-based workflow* means that a user can execute a full analysis, starting from raw data up to visualizations for publication, without any manual intervention. Ideally the main control file is a digital notebook following the literate programming paradigm (Knuth 1984), thereby integrating text, documentation, visualization, mapping (Giraud and Lambert 2017), and publication[7] in a coherent way. Jupyter (Kluyver et al. 2016; Rule et al. 2019) and R Markdown (Xie 2015) are the two most commonly used notebooks for practical reproducibility. Both support various programming languages, hybrid workflows, and operating systems. All of the workflow's parts can be openly published in the form of a *research compendium* (Gentleman and Temple Lang 2007), originally using a language's packaging mechanism and later extended and demonstrated as a powerful tool for scholarly communication.[8] A self-contained structured research compendium is "preproducible" (Stark 2018), connects the actual article with supplemental material (off-loading details; cf. Greenbaum et al. 2017), and becomes an executable research compendium (Nüst et al. 2017) if it includes both container and notebook. All parts of an (executable) research compendium must be adequately licensed to allow use and extension (cf.

Stodden 2009) and use open formats (Marwick 2015).

To summarize, authors, editors, reviewers, and publishers can achieve the highest reproducibility when they (1) familiarize themselves with common guidance for reproducible research (e.g., Sandve et al. 2013; The Turing Way Community et al. 2019), (2) consciously control computing environments, (3) use script-based workflows with notebooks, and (4) adhere to community practices for research compendia. These steps can bring researchers close to the "gold standard" end of Peng's (2011) reproducibility spectrum.

Using Reproducible Workflows

Based on a research compendium, reviewers, students, collaborators, and even the original authors years later can interact with a piece of research in a manner far beyond a classic "paper" article. Using a common format for a research compendium eases communication between authors and readers (Marwick, Boettiger, and Mullen 2018; Nüst, Boettiger, and Marwick 2018), and special infrastructures can be built to discover and interact with them (Perkel 2019). Research compendia can even underpin intelligent systems (cf. Santana-Perez and Pérez-Hernández 2015; Gil et al. 2016). There is not one special infrastructure emerging yet, nor should there be only one, because different approaches cater to different needs and communities and different actors—for example, publishers (Brunsdon 2016; Harris et al. 2017)—may provide it. For example, Code Ocean (Clyburne-Sherin, Fei, and Green 2019) is a commercial platform for researchers to conduct their work online based on Jupyter. It partners with publishers[9] to give reviewers and readers access to research compendia with a full development environment. Konkol and Kray (2019) described an enhanced examination workflow for scientific papers based on executable research compendia and used it to provide tailored interactive figures (Konkol, Kray, and Suleiman 2019). The Whole Tale (Brinckman et al. 2019) and BinderHub (Jupyter Project et al. 2018) projects build open platforms for reproducible research operated by research organizations. Such platforms are the most effective way today to leverage containerization for openly publishing practical, reproducible workflows and improving scholarly communication, without requiring additional expertise beyond creating research compendia.

Examples

The following examples illustrate the challenges, solutions, and prevailing shortcomings. They extend earlier collections of cases in geography (Brunsdon 2016), spatial data collection and analysis in ecology (Lewis, Wal, and Fifield 2018), spatial statistics[10] (Pebesma, Bivand, and Ribeiro 2015), and geosciences (Konkol, Kray, and Pfeiffer 2019).[11] A comprehensive reproducibility study in geography and geosciences is needed to substantiate these observations.

Spielman and Singleton (2015) studied neighborhoods with data from the American Community Survey and provided data and methods openly.[12] We applaud their efforts, which allowed us to partially reproduce the workflow,[13] such as setting a seed to avoid problems with nondeterministic results. This project, however, demonstrates typical shortcomings and issues for reproducibility (see also Konkol, Kray, and Pfeiffer 2019), such as lacking licenses, binary formats for data, and a data repository requiring login and acceptance of terms of use.

Marwick (2017) reported on a case study about the analysis of data from an archaeological excavation, with inherently geospatial data. In detail and suitable for a nontechnical audience, Marwick described all considerations and concrete actions for data archiving, scripting, publishing, and containerization of the computing environment.

Knoth and Nüst (2017) containerized a complex geographic object-based image analysis workflow using open source tools in a discipline where one proprietary software is ubiquitous. The work demonstrates how a combination of free tools can re-create a proprietary analysis workflow, and it shows how containerization can make it reusable by exposing configuration parameters and making the data set exchangeable.

Shannon and Walker (2018) described two case studies in housing and urban diversity for public-facing geographic research. The case studies entail *shiny*-based applications (Chang et al. 2020) with interactive plots and maps for nonexpert users to improve community engagement, which we could easily inspect and reproduce. The authors nicely use openness for transparency and provide synthetic data to handle data privacy, but the published code is sparsely documented and lacks licensing information, which hampers reuse and extension.

Verstegen (2019) published code and data for a land use change model based on PCRaster and a Python script (cf. Verstegen et al. 2012). The repository includes a container for ease of use and transparently communicates (despite lacking a notebook document) which parts of the workflow reproduce which figure and what changes were made to the code after the original article publication.

Challenges for Practical Reproducibility in Geography and Geosciences

Geography and geosciences are diverse disciplines, and their community members have equally diverse backgrounds, many of which do not include a familiarity with computational methods or software development. This diversity leads to challenges in adopting practical reproducibility in education and publishing. The focus on practical solutions in this work can inform these adaptations, which must be accompanied by changes of habits by individuals and at different organizational levels, such as research labs (cf. Nüst, Boettiger, and Marwick 2018). The large body of experience from other domains and best practices (Sandve et al. 2013; Stodden and Miguez 2014; Boettiger 2015; Eglen et al. 2017; Greenbaum et al. 2017; Marwick 2017; Eglen et al. 2018; Marwick, Boettiger, and Mullen 2018; Nüst et al. 2019; Pérignon et al. 2019; Rule et al. 2019; Schönbrodt 2019; Šimko et al. 2019) does not limit self-improvement and further training, but the amount of information might seem overwhelming. In a similar way, ongoing disruptions and innovations in scholarly publishing (cf. Gil et al. 2016; Singleton, Spielman, and Brunsdon 2016; Eglen et al. 2018; Tennant et al. 2019) pose challenges for geographers and geoscientists in their roles as authors, reviewers, and editors, especially for early career researchers and due to a complex mixture of community, commercial, and political interests.

Giraud and Lambert (2017) described the multiplicity of tools in the cartographic process as an impediment for reproducibility. They transferred Peng's spectrum into a spectrum of map reproducibility and set the equivalent of a research compendium (linked and executable code and data) at the highest level. They argued that cartography is often considered a design process and an art, but this should not be at the cost of reproducibility, for example, due to manual tweaking of visual appearances. Konkol, Kray, and Pfeiffer (2019) even found that the differences in the created maps were an effective way to assess reproducibility. Similar to the aforementioned spectra, Wilson et al. (2020) present a five-star classification for sharing geospatial research, addressing challenges in geographic information systems (GIS) software and algorithms.

Geospatial data and processing are often realized via spatial data infrastructures, such as the data, processing, and map interfaces by the Open Geospatial Consortium or OpenStreetMap. Online services pose a challenge for reproducibility, because they could change over time or disappear. A service-oriented approach, however, also promises improvement through standardization, less duplication of effort, and easier translation into different tools for cross-validation (Wilson et al. 2020). Still, the code to access geoservices and the requests sent as well as the retrieved responses must all be stored (cf. real-time data; Brunsdon 2016) to build a research compendium. When analyzing large data sets, processing is increasingly shifted to remote infrastructures closer to the data, which requires open availability not only of the application programming interface but also of the implementations (Hinz et al. 2013; Pebesma et al. 2017). "Free" platforms, such as Google Earth Engine, provide complex script-based processing to a broad audience, but the analyses are not reproducible because the computational environment cannot be captured or inspected in full (Sidhu, Pebesma, and Câmara 2018). When creating research compendia, compromises can be made as to the amount of detail they include to reduce storage size; for example, include only relevant data after preprocessing or allow referencing data in trusted data repositories or spatial data infrastructures (Nüst and Schutzeichel 2017).

Qualitative GIS was judged as nonreproducible by Preston and Wilson (2014), partially due to their mixed-methods approach. In our view, however, such an approach does not free researchers to work as reproducible as possible. Data collection and creation of visualizations can be reproducible and should be, because maps are commonly used for interaction with study participants during data collection and for communicating results. Muenchow, Schäfer, and Krüger (2019) reviewed the body of work in qualitative GIS research and identified reproducibility as having promising potential for the field.

Prevailing GIS software is based on a graphical user interface, proprietary, or both. To fix these limitations, either these tools must be updated to provide an executable workflow (i.e., recording a trace of the user interactions; cf. Brunsdon 2016) or researchers need to switch to open tools to achieve a unified toolchain (Giraud and Lambert 2017) and to avoid the risk of a digital divide but rather enable faster collaborative development (cf. Muenchow, Schäfer, and Krüger 2019). Proprietary software might in some cases be user friendly for conducting research, and Open Source alternatives require a higher computer literacy (Muenchow, Schäfer, and Krüger 2019), but such closed tools are ultimately unsuitable for science: No access to source code prohibits examination and extension of methods and can increase the potential of errors (Singleton, Spielman, and Brunsdon 2016) and restrictive nonopen license agreements prohibit reproduction by others without access or even by authors at a future point in time (Eaton 2012; Lees 2012; Singleton, Spielman, and Brunsdon 2016). Most important, open software stacks much better with core tools for practical reproducibility. The pace of digitization and the trend toward openness (cf. Nosek et al. 2015) put pressure on scientists at all career stages to switch to open tools[14] and require future geoscientists and geographers to be trained as "Pi-shaped researchers" with a deep knowledge both in their domain as well as in reproducibility and computing (Marwick 2017).

Limitations of sensitive data are commonly mentioned impediments to practical reproducibility, but various solutions exist. O'Loughlin et al. (2015) discussed the balance of disclosure and source protection in the field of political geography, and they mentioned redaction as a means to check research using quantitative data and statistical data rigorously. These limitations can also be seen as a need in establishing processes and providing infrastructure for controlled access to research compendia. Pérignon et al. (2019) and Foster (2018) described the tensions between reproducibility and data privacy, and they presented a public research infrastructure for confidential government data in France and cloud-based data enclaves. Shannon and Walker (2018) suggested an analysis infrastructure that restricts access to raw data and only provides derived results. In the context of geocomputation, Brunsdon argued the advantages of "'domains of reproducibility'—that is, groups of people who are permitted to access this information adopting reproducible practices amongst themselves—so that internal scrutiny, and updating of analyses becomes easier" (Harris et al. 2017, 608).

An approach to reduce the limitations induced by big, proprietary, export-controlled, or sensitive data is providing a synthetic data set (e.g., Shannon and Walker 2018). A data set of more manageable size reduces storage space as well as workflow execution time. Made-up data prevent deanonymization and can be tailored to illustrate the method. A copy of the original data within the research compendium ensures consistency and accessibility, but synthetic data, anonymized data, or data subsets allow third parties to evaluate, understand, validate, and build on methods.

Reproducibility of computational methods is further constrained by time. The fact that all presented platforms and tools are open themselves facilitates archival and maintenance, yet the reproduction of workflows in more than ten years is an open challenge beyond geography and geosciences. The Ten Years Challenge by the journal *ReScience*[15] is an example for learning more about problems and solutions for long-term reproducibility. Because we cannot foresee what future computers will look like, a research compendium that can be reproduced today, for example, as part of a peer review (Eglen and Nüst 2019) ensures that everything needed is there and ensures a starting point for future generations of geographers, geoscientists, and science historians.

Conclusions

In this article we describe practical solutions that facilitate computational reproducibility in scholarly communication. Wilson and Burrough (1999) stated on a new geography, "It is also clear that improved understanding of landscapes comes … from the study of large quantities of data in a reproducible data-handling environment that extends from the field to the laboratory and the computer" (743). They further argued for the adoption of new methods and that "geographers will need to be comfortable in new sneakers that incorporate the [new methods]" (Wilson and Burrough 1999, 743). As the new method, we suggest replacing traditional text-centric research papers as the final product of research with executable research compendia: digital artifacts that encapsulate the data, the script-based workflow and its computing environment, and the article based on a notebook.

The emerging infrastructure for research compendia greatly reduces the needed software engineering skills, yet a lack of academic recognition for openness and reproducibility and a lack of hard, minimal requirements posed by editorial boards of scientific journals still keep scientists from adopting methods supporting practical reproducibility. Chen et al. (2019) rightly argued that new research practices must be tailored to the needs of scientific disciplines. In geography and geosciences, this discourse has just started (Pebesma, Nüst, and Bivand 2012a, 2012b; Gil et al. 2016; Nüst, Boettiger, and Marwick 2018; Kedron et al. 2019, and the articles of this Forum). These scientific communities must decide which degree of reproducibility is "good enough," but we believe that in most cases "very, very close to the original" is feasible and practical. Irrespective of whether the "reproducibility crisis" does or does not exist (cf. Fanelli 2018), the benefits of working reproducibly are by now clear. Technical, systemic, and cultural barriers are conquerable. The advantages of reproducibility for scientific progress lie in strengthened trust in results through transparency, higher productivity through openness, and more innovation through collaboration and exploration of new pathways. The scientific community should embrace the disruptions in scholarly publishing and reap the benefits and advantages by setting up new platforms and standards for scholarly communication (e.g., Munafò et al. 2017; Kray et al. 2019). The maxim of the new technology for practical reproducibility should be open source software implementing an open and self-correcting public infrastructure controlled by scientists (cf. Buck 2015; Santana-Perez and Pérez-Hernández 2015; Munafò et al. 2017).

Acknowledgments

We thank Celeste R. Brennecka from the Scientific Editing Service, University of Münster, for her editorial review. Two anonymous reviewers provided valuable comments on an earlier version of this article. We thank the organizers of the workshop on Reproducibility and Replicability in Geospatial Research at Arizona State University and of the subsequent Forum for the opportunities to contribute.

Funding

This work is supported by the project Opening Reproducible Research II (https://www.uni-muenster.de/forschungaz/project/12343) funded by the German Research Foundation (DFG) under project number PE 1632/17-1.

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Notes

1. *Reproduction* means that the authors' materials are available for third parties to re-create identical results, whereas replication means different data and methods lead to the same findings. From a computational standpoint, *identical* is more complicated than it sounds; for example, floating point computations might result in small yet insignificant numerical differences, or image-rendering algorithms might introduce nondeterministic artifacts.
2. For example, CRAN (https://cran.r-project.org) and renv (https://cran.r-project.org/package = renv) for R, or PyPI (https://pypi.org/) and conda (https://conda.io) for Python, which even has tooling for separating full installations in virtual environments; for example, virtualenv (https://virtualenv.pypa.io).
3. For the simplicity of the argument, we use *recipe* instead of Dockerfile and *containers* as a catch-all term, whereas the experienced reader might expect a distinction between *container* and *image*.
4. Docker is the most common containerization solution today (see https://en.wikipedia.org/wiki/Docker_(software)). It is open source, and relevant parts are standardized (see https://www.opencontainers.org/).
5. Singularity is mostly used in scientific contexts and high-performance computing, see Kurtzer, Sochat, and Bauer (2017).
6. Proprietary software cannot be avoided in some areas, such as the system BIOS or device drivers.
7. The notebook might render directly into submission-ready manuscripts with R Markdown and the *rticles* package by Allaire et al. (2020), which supports a variety of journals, including the publisher of the *Annals*, Taylor & Francis, and other publishers close to the disciplines such as AGU or Copernicus Publications (EGU).
8. See https://research-compendium.science/ for a minimal definition, extensive literature, and examples.

The R (R Core Team 2019) community is at the forefront of enabling reproducibility both in the available tools and in the mindset of the user community (e.g., Pebesma, Nüst, and Bivand 2012b; Marwick 2015).
9. For example, Sage (Estop 2019), De Gruyter (Code Ocean 2018), or Nature ("Easing the Burden of Code Review" 2018).
10. All articles in this special issue on software for spatial statistics in the *Journal of Statistical Software* are in principle reproducible, but these articles by software developers are probably not representative of the whole community using the software.
11. The largest study to date, it reproduced thirty-one research articles. See the full list at https://osf.io/sfqjg/.
12. Code on GitHub: https://github.com/geoss/acs_demographic_clusters; data on openICPSR: http://doi.org/10.3886E41329V1.
13. A summary of the issues, changes, suggestions, and subsequent communication with the authors is available at https://github.com/geoss/acs_demographic_clusters/issues/2.
14. The Carpentries (https://carpentries.org/) is an excellent resource to learn data science skills outside of topical studies.
15. See https://rescience.github.io/ten-years/.

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