REPRODUCIBILITY AND REPLICABILITY FORUM

Practical Reproducibility in Geography and Geosciences

Daniel Nüst[a] and Edzer Pebesma[a]

[a]Institute for Geoinformatics, University of Münster, 48149 Münster, Germany

This is an Accepted Manuscript of an article published online by Taylor & Francis in *Annals of the American Association of Geographers* on 13 Oct 2020, available online: `https://doi.org/10.1080/24694452.2020.1806028`.

ABSTRACT

Reproducible research is often perceived as a technological challenge, but it is rooted in the challenge to improve scholarly communication in an age of digitisation. When computers become involved and researchers want to allow other scientists to inspect, understand, evaluate, and build upon 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 containerisation, while paying attention to working with geospatial data (digital maps, GIS). 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 and communities adopt reproducibility and the underlying technologies in practice and in policies, they can transform the way researchers conduct and communicate their work towards increased transparency, understandability, openness, trust, productivity, and innovation.

KEYWORDS

computational reproducibility; reproducible research; scholarly communication;

Introduction

Reproducible research is often perceived as primarily a technological challenge, but is really rooted in the challenge to adjust scholarly communication to today's level of digitisation and diversity of scientific outputs. Common academic challenges, e.g., 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 (2018) and Nüst et al. (2018) respectively, and both studies show that it needs to improve. Other fields support this result, e.g., Brunsdon (2016) for quantitative geography, Wainwright (2020) with an informal search in critical geography, Sui and Kedron (2020) discuss the conceptual challenges of reproducibility and replication in geography, and Sui and Shaw (2018) discuss 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

CONTACT D. Nüst. Email: daniel.nuest@uni-muenster.de

All URLs in this manuscript have been last accessed April 24, 2020.

benefits of reproducibility (Donoho 2010; Markowetz 2015; Vandewalle, Kovacevic, and Vetterli 2009; Marwick 2015; Kray et al. 2019) and the innovative potential of working reproducibly, which comprise 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 (Nüst et al. 2018; Munafò et al. 2017). 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 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, i.e., that datasets used can be re-collected or computations can be repeated (Peng 2011). In studies describing particular areas and time periods of the Earth, this may 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 may 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 a scientific claim can be evaluated and becomes a minimal standard (Peng 2011; Sandve et al. 2013). Open data alone does 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 make it particularly important that concerns around computational reproducibility, i.e., 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'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 paraphrases Claerbout and Karrenbach (1992)).

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

[1]Reproduction means the authors' materials are available for third parties to recreate 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, e.g., floating point computations may result in small yet insignificant numerical differences, or image rendering algorithms may introduce non-deterministic artefacts.

Reproducible workflows in geography and geosciences

Creating reproducible workflows

Scientists must realise how fragile the typical research workflows are today. We've 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) present 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) describe 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 upon 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 hard- 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 may be crafted manually, generated with the assistance of tools (e.g., Jupyter Project et al. 2018; Nüst and Hinz 2019), or recorded as provenance, e.g., 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 the 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 sections Examples and Conclusions cover the *cultural component*.

The *physical component* is the hardware, e.g., the researcher's laptop, a university's high-performance computing facility, a GPS 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 (see Section Introduction), 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 lifespan than hardware, and outdated hardware can often, though much later, be emulated by software.

To capture the *logical component*, common software development methods, i.e. 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. Virtualisation (Howe 2012) and containerisation[3] (Boettiger 2015) provide adequate solutions to capture full software stacks, i.e., both programs researchers are aware of 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, cf.), 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],

[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, e.g., `virtualenv` (https://virtualenv.pypa.io).

[3]For the simplicity of the argument, we use "recipe" instead of `Dockerfile` and "containers" as a catchall term, whereas the experienced reader may expect a distinction between "container" and "image".

[4]Docker is the most common containerisation solution today, see https://en.wikipedia.org/wiki/Docker_(software). It is

Singularity[5], or supportive automating tools (Jupyter Project et al. 2018) is a core skill for geoscientists and geographers analysing or visualising data with computers.

The goal of describing the computing environment is to allow others to recreate, scrutinise, or extend it. This becomes more difficult when (a) the logical component is directly linked with the physical component, e.g., bespoke optimised software for a particular computing infrastructure, such as high performance computing, or (b) critical parts of the computations involve proprietary software[6] (cf. Section Challenges for practical reproducibility in geography and geosciences).

A **script-based workflow** means that a user can execute a full analysis, i.e., starting from raw data up to visualisations for publication, without any manual intervention. Ideally the main control file is a digital *notebook* following the literate programming paradigm (Knuth 1984) and thereby integrates text, documentation, visualisation, 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 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[2] 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 highest reproducibility when they (i) familiarise themselves with common guidance for reproducible research (e.g., Sandve et al. 2013; The Turing Way Community et al. 2019), (ii) consciously control computing environments, (iii) use script-based workflows with notebooks, and (iv) adhere to community practices for research compendia. These steps can bring researchers close to the *"gold standard"* end of Peng's reproducibility spectrum (Peng 2011).

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 (Nüst, Boettiger, and Marwick 2018), and special infrastructures can be built to discover and interact with them (Perkel 2019). RC can even underpin intelligent systems (cf. Gil et al. 2016; Santana-Perez and Pérez-Hernández 2015). There is not one special infrastructure emerging yet, nor should there be only one, as different approaches cater to different needs and communities and different actors, e.g., publishers (Harris et al. 2017; Brunsdon 2016), 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 and partners with publishers[9] to give reviewers and readers access to research compendia with a full development environment. Konkol and Kray (2019) describe an enhanced examination workflow for scientific papers based on executable research compendia and use it to provide tailored interactive figures (Konkol, Kray, and Suleiman 2019). The Whole Tale (Brinckman et al. 2019) and

open source, and relevant parts standardised, 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 may 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 of the AAG, 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 (Editorial 2018).

BinderHub (Jupyter Project et al. 2018) projects build open platforms for reproducible research operated by research organisations. Such platforms are the most effective way today to leverage containerisation for openly publishing practical reproducible workflows and improve 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 2018[11]). A comprehensive reproducibility study in geography and geosciences is needed to substantiate these observations.

Spielman and Singleton (2015) study neighborhoods with data from the American Community Survey and provide data and methods openly[12]. We applaud the authors's efforts, which allowed us to partially reproduce the workflow[13], such as setting a seed to avoid problems with non-deterministic results. This project, however, demonstrates typical shortcomings and issues for reproducibility (see also Konkol, Kray, and Pfeiffer 2018), such as lacking licenses, binary formats for data, and a data repository requiring login and acceptance of terms of use.

Marwick (2017) reports on a case study about the analysis of data from an archaeological excavation, with inherently geospatial data. In detail and suitable for a non-technical audience, Marwick describes all considerations and concrete actions for data archiving, scripting, publishing, and containerisation 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 recreate a proprietary analysis workflow, and it shows how containerisation can make it re-usable by exposing configuration parameters and making the dataset exchangeable.

Shannon and Walker (2018) describe 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 non-experts 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. article Verstegen et al. 2012). The repository includes a container for ease of use and transparently communicates (despite lacking a notebook document) the 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 bring along 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

[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 31 research articles, see full list at https://osf.io/sfqjg/.

[12] Code on GitHub: https://github.com/geoss/acs_demographic_clusters; data on openICPSR: http://doi.org/10.3886/E41329V1.

[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.

organisational levels, such as research labs (cf. Nüst et al. 2018). The large body of experience from other domains and best practices (Eglen et al. 2018; Stodden and Miguez 2014; Nüst et al. 2019; Sandve et al. 2013; Boettiger 2015; Rule et al. 2019; Schönbrodt 2019; Greenbaum et al. 2017; Marwick, Boettiger, and Mullen 2018; Eglen et al. 2017; Šimko et al. 2019; Pérignon et al. 2019; Marwick 2017) do 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. Tennant et al. 2019; Eglen et al. 2018; Gil et al. 2016; Singleton, Spielman, and Brunsdon 2016) 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) describe the multiplicity of tools in the *cartographic process* an impediment for reproducibility. They transfer Peng's spectrum into a *spectrum of map reproducibility* and set the equivalent of a research compendium (linked & executable code and data) at the highest level. They argue that cartography is often considered a design process and an art, but this should not be at the cost of reproducibility, e.g., due to manual tweaking of visual appearances. Konkol, Kray, and Pfeiffer (2018) 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 5-star classification for sharing geospatial research, addressing challenges in GIS software and algorithms.

Geospatial data and processing are often realised via Spatial Data Infrastructures (SDI), such as the data, processing, and map interfaces by the Open Geospatial Consortium (OGC) or OpenStreetMap. Online services pose a challenge for reproducibility, because they may change over time or disappear. But a service-oriented approach also promises improvement through standardization, less duplication of efforts, and easier translation into different tools for cross-validation (Wilson et al. 2020). Still, the code to access geoservices, the requests sent as well as the retrieved responses must all be stored (cf. real-time data Brunsdon 2016) in order to build a research compendium. When analysing large data sets, processing is increasingly shifted to remote infrastructures closer to the data, which requires open availability not only of the API, but also of the implementations (Pebesma et al. 2017; Hinz et al. 2013). "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 may be made as to the amount of detail they includes to reduce storage size, e.g., include only relevant data after preprocessing, or allow referencing data in trusted data repositories or SDIs (Nüst and Schutzeichel 2017).

Qualitative GIS is judged as non-reproducible by Preston and Wilson (2014), partially due to their mixed-methods approach. However, in our view such an approach does not free researchers to work as reproducible as possible. Data collection and creation of visualisations 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) review the body of work in qualitative GIS research and identify reproducibility as having promising potential for the field.

Prevailing *GIS software* is GUI based, 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 may 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); restrictive non-open license agreements prohibit reproduction, e.g., by others without access or even by authors at a future point in time (Lees 2012; Eaton 2012; Singleton, Spielman, and Brunsdon 2016). Most importantly, open software stacks much better with core tools for practical reproducibility (see Section Creating reproducible workflows). The pace of digitisation and the trend towards 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) discuss the balance of disclosure and source protection in the field of political geography, and they mention redaction as a means to check research using quantitative data and statistical data rigorously. These limitations can also be seen as a need of establishing processes and providing infrastructure for controlled access to research compendia. Pérignon et al. (2019) and Foster (2018) describe the tensions between reproducibility and data privacy, and they present a public research infrastructure for confidential government data in France respectively cloud-based data enclaves. Shannon and Walker (2018) suggest an analysis infrastructure that restricts access to raw data and only provides derived results. In the context of geocomputation, C. Brunsdon argues 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, p. 608).

An approach to reduce the limitations induced by big, proprietary, export controlled, or sensitive data is providing a synthetic dataset (e.g., Shannon and Walker 2018). A dataset of more manageable size reduces storage space as well as workflow execution time. Made-up data prevents de-anonymisation and can be tailored to illustrate the method. While a copy of the original data within the research compendium ensures consistency and accessibility, synthetic data, anonymised data, or data subsets allow third parties to evaluate, understand, validate, and build upon 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. Since we cannot foresee what future computers will look like, a research compendium that can be reproduced today, e.g. 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 stated in 1999 (p. 743) 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."* 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]"* (ibid., p. 743). As the new method, we suggest to replace traditional text-centric research papers as the final product of research with executable research compendia: digital artefacts 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 argue

[14]The Carpentries (https://carpentries.org/) are an excellent resource to learn data science skills outside of topical studies.
[15]https://rescience.github.io/ten-years/

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,b; Gil et al. 2016; Nüst et al. 2018; Kedron et al. 2019, and the articles of this Annals 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 the 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., Kray et al. 2019; Munafò et al. 2017). 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).

Disclosure statement

No potential conflict of interest was reported by the authors.

Acknowledgements

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. 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 organisers of the workshop on Reproducibility and Replicability in Geospatial Research at Arizona State University and of the subsequent Forum for the opportunities to contribute.

Biographical notes

DANIEL NÜST is researcher at the Institute for Geoinformatics, University of Münster, 48149 Münster, Germany. E-mail: daniel.nuest@uni-muenster.de. He completed his studies in Münster with a Diploma in Geoinformatics and worked at 52°North Initiative for Geospatial Open Source Software as a consultant and software developer. Since 2016, Daniel develops tools for creation and execution of research compendia in geography and geosciences in the project *Opening Reproducible Research* (o2r, https://o2r.info). He is Reproducibility Chair at the AGILE Conference 2020.

EDZER PEBESMA is professor of Geoinformatics at University of Münster, 48149 Münster, Germany, since 2007. E-mail: edzer.pebesma@uni-muenster.de. He is developer and maintainer of several popular R packages for handling and analyzing spatial and spatiotemporal data (`sp`, `spacetime`, `gstat`, `sf`), co-author of the book Applied Spatial Data Analysis with R, and active member of the R-sig-Geo/r-spatial community. He is Co-Editor-in-Chief for the Journal of Statistical Software.

References

Allaire, JJ, Yihui Xie, R Foundation, Hadley Wickham, Journal of Statistical Software, Ramnath Vaidyanathan, Association for Computing Machinery, et al. 2020. *rticles: Article Formats for R Markdown*. CRAN. R package version 0.14.1, Accessed 2020-08-31. https://github.com/rstudio/rticles.

Barba, Lorena A. 2018. "Terminologies for Reproducible Research." *arXiv:1802.03311 [cs]* http://arxiv.org/abs/1802.03311.

Barnes, Nick. 2010. "Publish your computer code: it is good enough." *Nature News* 467 (7317): 753–753. https://doi.org/10.1038/467753a.

Bhandari Neupane, Jayanti, Ram P. Neupane, Yuheng Luo, Wesley Y. Yoshida, Rui Sun, and Philip G. Williams. 2019. "Characterization of Leptazolines A–D, Polar Oxazolines from the Cyanobacterium Leptolyngbya sp., Reveals a Glitch with the "Willoughby–Hoye" Scripts for Calculating NMR Chemical Shifts." *Organic Letters* https://doi.org/10.1021/acs.orglett.9b03216.

Boettiger, Carl. 2015. "An Introduction to Docker for Reproducible Research." *ACM SIGOPS Operating Systems Review* 49 (1): 71–79. https://doi.org/10.1145/2723872.2723882.

Brinckman, Adam, Kyle Chard, Niall Gaffney, Mihael Hategan, Matthew B. Jones, Kacper Kowalik, Sivakumar Kulasekaran, et al. 2019. "Computing environments for reproducibility: Capturing the "Whole Tale"." *Future Generation Computer Systems* 854–867. https://doi.org/10.1016/j.future.2017.12.029.

Brunsdon, Chris. 2016. "Quantitative methods I: Reproducible research and quantitative geography." *Progress in Human Geography* 40 (5): 687–696. https://doi.org/10.1177/0309132515599625.

Buck, Stuart. 2015. "Solving reproducibility." *Science* 348 (6242): 1403–1403. https://doi.org/10.1126/science.aac8041.

Chang, Winston, Joe Cheng, J. J. Allaire, Yihui Xie, and Jonathan McPherson. 2020. *shiny: Web Application Framework for R*. CRAN. R package version 1.4.0.2, Accessed 2020-08-31. https://CRAN.R-project.org/package=shiny.

Chen, Xiaoli, Sünje Dallmeier-Tiessen, Robin Dasler, Sebastian Feger, Pamfilos Fokianos, Jose Benito Gonzalez, Harri Hirvonsalo, et al. 2019. "Open is not enough." *Nature Physics* 15 (2): 113. https://doi.org/10.1038/s41567-018-0342-2.

Claerbout, J., and M. Karrenbach. 1992. "Electronic documents give reproducible research a new meaning." In *SEG Technical Program Expanded Abstracts 1992*, SEG Technical Program Expanded Abstracts, 601–604. Tulsa, OK, USA: Society of Exploration Geophysicists. https://doi.org/10.1190/1.1822162.

Clyburne-Sherin, April, Xu Fei, and Seth Ariel Green. 2019. "Computational Reproducibility via Containers in Psychology." *Meta-Psychology* 3. https://doi.org/10.15626/MP.2018.892.

Code Ocean. 2018. "De Gruyter Partners with Code Ocean to Improve Research Reproducibility." Accessed 2020-04-24. https://codeocean.com/press-release/de-gruyter-partners-with-code-ocean-to-improve-research-reproducibility.

Donoho, David L. 2010. "An invitation to reproducible computational research." *Biostatistics* 11 (3): 385–388. https://doi.org/10.1093/biostatistics/kxq028.

Eaton, John W. 2012. "GNU Octave and reproducible research." *Journal of Process Control* 22 (8): 1433–1438. https://doi.org/10.1016/j.jprocont.2012.04.006.

Editorial, Nature Methods. 2018. "Easing the burden of code review." *Nature Methods* 15 (9): 641–641. https://doi.org/10.1038/s41592-018-0137-5.

Eglen, Stephen, and Daniel Nüst. 2019. "CODECHECK: An open-science initiative to facilitate sharing of computer programs and results presented in scientific publications." In *The 14th Munin Conference on Scholarly Publishing 2019*, Septentrio Conference Series. University Library, UiT The Arctic University of Norway. https://doi.org/10.7557/5.4910.

Eglen, Stephen J., Ben Marwick, Yaroslav O. Halchenko, Michael Hanke, Shoaib Sufi, Padraig Gleeson, R. Angus Silver, et al. 2017. "Toward standard practices for sharing computer code and programs in neuroscience." *Nature Neuroscience* 20 (6): 770–773. https://doi.org/10.1038/nn.4550.

Eglen, Stephen J., Ross Mounce, Laurent Gatto, Adrian M. Currie, and Yvonne Nobis. 2018. "Recent developments in scholarly publishing to improve research practices in the life sciences." *Emerging Topics in Life Sciences* 2 (6): 775–778. https://doi.org/10.1042/ETLS20180172.

Emsley, Iain, and David De Roure. 2018. "A Framework for the Preservation of a Docker Container | International Journal of Digital Curation." *International Journal of Digital Curation* 12 (2). https://doi.org/10.2218/ijdc.v12i2.509.

Estop, Heather. 2019. “SAGE trials Code Ocean to improve research reproducibility.” Accessed 2020-04-24. https://journalsblog.sagepub.com/blog/sage-trials-code-ocean-to-improve-research-reproducibility.

Fanelli, Daniele. 2018. “Opinion: Is science really facing a reproducibility crisis, and do we need it to?” *Proceedings of the National Academy of Sciences* 201708272. https://doi.org/10.1073/pnas.1708272114.

Foster, Ian. 2018. “Research Infrastructure for the Safe Analysis of Sensitive Data.” *The ANNALS of the American Academy of Political and Social Science* 675 (1): 102–120. https://doi.org/10.1177/0002716217742610.

Gentleman, Robert, and Duncan Temple Lang. 2007. “Statistical Analyses and Reproducible Research.” *Journal of Computational and Graphical Statistics* 16 (1): 1–23. https://doi.org/10.1198/106186007X178663.

Gil, Yolanda, Cédric H. David, Ibrahim Demir, Bakinam T. Essawy, Robinson W. Fulweiler, Jonathan L. Goodall, Leif Karlstrom, et al. 2016. “Toward the Geoscience Paper of the Future: Best practices for documenting and sharing research from data to software to provenance.” *Earth and Space Science* 3 (10): 388–415. https://doi.org/10.1002/2015EA000136.

Giraud, Timothée, and Nicolas Lambert. 2017. “Reproducible Cartography.” In *Advances in Cartography and GIScience*, edited by Michael P. Peterson, Lecture Notes in Geoinformation and Cartography, 173–183. Springer, Cham. https://doi.org/10.1007/978-3-319-57336-6_13.

Greenbaum, Dov, Joel Rozowsky, Victoria Stodden, and Mark Gerstein. 2017. “Structuring supplemental materials in support of reproducibility.” *Genome Biology* 18 (1): 64. https://doi.org/10.1186/s13059-017-1205-3.

Gronenschild, Ed H. B. M., Petra Habets, Heidi I. L. Jacobs, Ron Mengelers, Nico Rozendaal, Jim van Os, and Machteld Marcelis. 2012. “The Effects of FreeSurfer Version, Workstation Type, and Macintosh Operating System Version on Anatomical Volume and Cortical Thickness Measurements.” *PLOS ONE* 7 (6): e38234. http://doi.org/10.1371/journal.pone.0038234.

Harris, Richard, David O’Sullivan, Mark Gahegan, Martin Charlton, Lex Comber, Paul Longley, Chris Brunsdon, et al. 2017. “More bark than bytes? Reflections on 21+ years of geocomputation.” *Environment and Planning B: Urban Analytics and City Science* 44 (4): 598–617. https://doi.org/10.1177/2399808317710132.

Higman, Rosie, Daniel Bangert, and Sarah Jones. 2019. “Three camps, one destination: the intersections of research data management, FAIR and Open.” *Insights* 32 (1): 1–9. https://doi.org/10.1629/uksg.468.

Hinz, Matthias, Daniel Nüst, Benjamin Proß, and Edzer Pebesma. 2013. “Spatial Statistics on the Geospatial Web.” In *The 16th AGILE International Conference on Geographic Information Science, Short Papers*, edited by Danny Vandenbroucke, Bénédicte Bucher, and Joep Crompvoets, Leuven, Belgium, 1–7. AGILE. https://doi.org/10.31223/osf.io/j8x2e.

Hirst, Tony. 2019. “Fragment — Some Rambling Thoughts on Computing Environments in Education.” Accessed 2020-04-24. https://blog.ouseful.info/2019/03/20/fragment-some-rambling-thoughts-on-computing-environments-in-education/.

Howe, B. 2012. “Virtual Appliances, Cloud Computing, and Reproducible Research.” *Computing in Science Engineering* 14 (4): 36–41. https://doi.org/10.1109/MCSE.2012.62.

Jupyter Project, Matthias Bussonnier, Jessica Forde, Jeremy Freeman, Brian Granger, Tim Head, Chris Holdgraf, et al. 2018. “Binder 2.0 - Reproducible, interactive, sharable environments for science at scale.” *Proceedings of the 17th Python in Science Conference* 113–120. https://doi.org/10.25080/Majora-4af1f417-011.

Kedron, Peter, Amy E. Frazier, Andrew B. Trgovac, Trisalyn Nelson, and A. Stewart Fotheringham. 2019. “Reproducibility and Replicability in Geographical Analysis.” *Geographical Analysis* (Accepted/In press). https://doi.org/10.1111/gean.12221.

Kluyver, Thomas, Benjamin Ragan-Kelley, Fernando Pérez, Brian Granger, Matthias Bussonier, Jonathan Frederic, Kyle Kelley, et al. 2016. “Jupyter Notebooks - a publishing format for reproducible computational workflows.” In *Proceedings of the 20th International Conference on Electronic Publishing*, edited by Fernando Loizides and Birgit Schmidt, Amsterdam, Netherlands, 87–90. https://doi.org/10.3233/978-1-61499-649-1-87.

Knoth, Christian, and Daniel Nüst. 2017. “Reproducibility and Practical Adoption of GEOBIA with Open-Source Software in Docker Containers.” *Remote Sensing* 9 (3): 290. https://doi.org/10.3390/rs9030290.

Knuth, Donald E. 1984. “Literate Programming.” *The Computer Journal* 27 (2): 97–111. https://doi.

org/10.1093/comjnl/27.2.97.
Konkol, Markus, and Christian Kray. 2019. "In-depth examination of spatiotemporal figures in open reproducible research." *Cartography and Geographic Information Science* 46 (5): 412–427. https://doi.org/10.1080/15230406.2018.1512421.
Konkol, Markus, Christian Kray, and Max Pfeiffer. 2018. "Computational reproducibility in geoscientific papers: Insights from a series of studies with geoscientists and a reproduction study." *International Journal of Geographical Information Science* 33 (2): 408–429. https://doi.org/10.1080/13658816.2018.1508687.
Konkol, Markus, Christian Kray, and Jan Suleiman. 2019. "Creating Interactive Scientific Publications Using Bindings." *Proceedings of the ACM on Human-Computer Interaction* 3 (EICS): 16:1–16:18. http://doi.acm.org/10.1145/3331158.
Kray, Christian, Edzer Pebesma, Markus Konkol, and Daniel Nüst. 2019. "Reproducible Research in Geoinformatics: Concepts, Challenges and Benefits (Vision Paper)." In *14th International Conference on Spatial Information Theory (COSIT 2019)*, edited by Sabine Timpf, Christoph Schlieder, Markus Kattenbeck, Bernd Ludwig, and Kathleen Stewart, Vol. 142 of *Leibniz International Proceedings in Informatics (LIPIcs)*, Dagstuhl, Germany, 8:1–8:13. Schloss Dagstuhl–Leibniz-Zentrum fuer Informatik. https://doi.org/10.4230/LIPIcs.COSIT.2019.8.
Kurtzer, Gregory M., Vanessa Sochat, and Michael W. Bauer. 2017. "Singularity: Scientific containers for mobility of compute." *PLOS ONE* 12 (5): e0177459. https://10.1371/journal.pone.0177459.
Lees, Jonathan M. 2012. "Open and Free: Software and Scientific Reproducibility." *Seismological Research Letters* 83 (5): 751–752. https://doi.org/10.1785/0220120091.
Lewis, Keith P., Eric Vander Wal, and David A. Fifield. 2018. "Wildlife biology, big data, and reproducible research." *Wildlife Society Bulletin* 42 (1): 172–179. https://doi.org/10.1002/wsb.847.
Markowetz, Florian. 2015. "Five selfish reasons to work reproducibly." *Genome Biology* 16: 274. https://doi.org/10.1186/s13059-015-0850-7.
Marwick, Ben. 2015. "How computers broke science – and what we can do to fix it." Accessed 2020-04-24. https://theconversation.com/how-computers-broke-science-and-what-we-can-do-to-fix-it-49938.
Marwick, Ben. 2017. "Computational Reproducibility in Archaeological Research: Basic Principles and a Case Study of Their Implementation." *Journal of Archaeological Method and Theory* 24 (2): 424–450. https://doi.org/10.1007/s10816-015-9272-9.
Marwick, Ben, Carl Boettiger, and Lincoln Mullen. 2018. "Packaging Data Analytical Work Reproducibly Using R (and Friends)." *The American Statistician* 72 (1): 80–88. https://doi.org/10.1080/00031305.2017.1375986.
Muenchow, Jannes, Susann Schäfer, and Eric Krüger. 2019. "Reviewing qualitative GIS research—Toward a wider usage of open-source GIS and reproducible research practices." *Geography Compass* 13 (6): e12441. https://onlinelibrary.wiley.com/doi/abs/10.1111/gec3.12441.
Munafò, Marcus R., Brian A. Nosek, Dorothy V. M. Bishop, Katherine S. Button, Christopher D. Chambers, Nathalie Percie du Sert, Uri Simonsohn, Eric-Jan Wagenmakers, Jennifer J. Ware, and John P. A. Ioannidis. 2017. "A manifesto for reproducible science." *Nature Human Behaviour* 1 (1): 1–9. https://www.nature.com/articles/s41562-016-0021.
National Academies of Sciences, Engineering, and Medicine. 2019. *Reproducibility and Replicability in Science*. National Academies Press. https://doi.org/10.17226/25303.
Nosek, B. A., G. Alter, G. C. Banks, D. Borsboom, S. D. Bowman, S. J. Breckler, S. Buck, et al. 2015. "Promoting an open research culture." *Science* 348 (6242): 1422–1425. https://doi.org/10.1126/science.aab2374.
Nüst, Daniel, and Marc Schutzeichel. 2017. "An Architecture for Reproducible Computational Geosciences." In *Poster abstracts of AGILE 2017*, Wageningen, The Netherlands, Jun. https://doi.org/10.5281/zenodo.1478542.
Nüst, Daniel, Carl Boettiger, and Ben Marwick. 2018. "How to Read a Research Compendium." *arXiv:1806.09525 [cs]* ArXiv: 1806.09525, http://arxiv.org/abs/1806.09525.
Nüst, Daniel, Carlos Granell, Barbara Hofer, Markus Konkol, Frank O. Ostermann, Rusne Sileryte, and Valentina Cerutti. 2018. "Reproducible research and GIScience: an evaluation using AGILE conference papers." *PeerJ* 6: e5072. https://doi.org/10.7717/peerj.5072.
Nüst, Daniel, and Matthias Hinz. 2019. "containerit: Generating Dockerfiles for reproducible research with R." *Journal of Open Source Software* 4 (40): 1603. https://doi.org/10.21105/joss.01603.
Nüst, Daniel, Markus Konkol, Edzer Pebesma, Christian Kray, Marc Schutzeichel, Holger Przibytzin, and Jörg Lorenz. 2017. "Opening the Publication Process with Executable Research Compendia." *D-Lib*

Magazine 23 (1/2). https://doi.org/10.1045/january2017-nuest.

Nüst, Daniel, Frank Ostermann, Rusne Sileryte, Barbara Hofer, Carlos Granell, Marta Teperek, Anita Graser, Karl Broman, and Kristina Hettne. 2019. *AGILE Reproducible Paper Guidelines.* Web: OSF. https://doi.org/10.17605/OSF.IO/CB7Z8.

O'Loughlin, John, Pauliina Raento, Joanne P. Sharp, James D. Sidaway, and Philip E. Steinberg. 2015. "Data ethics: Pluralism, replication, conflicts of interest, and standards in Political Geography." *Political Geography* 44: A1–A3. https://doi.org/10.1016/j.polgeo.2014.11.001.

Pebesma, Edzer, Roger Bivand, and Paulo Justiniano Ribeiro. 2015. "Software for Spatial Statistics." *Journal of Statistical Software* 63 (1): 1–8. https://doi.org/10.18637/jss.v063.i01.

Pebesma, Edzer, Daniel Nüst, and Roger Bivand. 2012a. "R for reproducible geographical research." Presented at the AAG Annual Meeting 2012, Feb 24, 2012, New York, NY, USA, Accessed 2020-08-31. http://pebesma.staff.ifgi.de/r_repr.pdf.

Pebesma, Edzer, Daniel Nüst, and Roger Bivand. 2012b. "The R software environment in reproducible geoscientific research." *Eos, Transactions American Geophysical Union* 93 (16): 163–163. https://doi.org/10.1029/2012EO160003.

Pebesma, Edzer, Wolfgang Wagner, Matthias Schramm, Alexandra Von Beringe, Christoph Paulik, Markus Neteler, Johannes Reiche, et al. 2017. "OpenEO - a Common, Open Source Interface Between Earth Observation Data Infrastructures and Front-End Applications." Web. https://doi.org/10.5281/zenodo.1065474.

Peng, Roger D. 2011. "Reproducible Research in Computational Science." *Science* 334 (6060): 1226–1227. https://doi.org/10.1126/science.1213847.

Perkel, Jeffrey M. 2019. "Make code accessible with these cloud services." *Nature* 575: 247–248. https://doi.org/10.1038/d41586-019-03366-x.

Piwowar, Heather. 2013. "Altmetrics: Value all research products." *Nature* 493: 159. https://doi.org/10.1038/493159a.

Preston, Bryan, and Matthew W. Wilson. 2014. "Practicing GIS as Mixed Method: Affordances and Limitations in an Urban Gardening Study." *Annals of the Association of American Geographers* 104 (3): 510–529. https://doi.org/10.1080/00045608.2014.892325.

Pérignon, Christophe, Kamel Gadouche, Christophe Hurlin, Roxane Silberman, and Eric Debonnel. 2019. "Certify reproducibility with confidential data." *Science* 365 (6449): 127–128. https://doi.org/10.1126/science.aaw2825.

R Core Team. 2019. *R: A Language and Environment for Statistical Computing.* Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Ram, Karthik. 2013. "Git can facilitate greater reproducibility and increased transparency in science." *Source Code for Biology and Medicine* 8 (1): 7. https://doi.org/10.1186/1751-0473-8-7.

Rechert, Klaus, Thomas Liebetraut, Stefan Kombrink, Dennis Wehrle, Susanne Mocken, and Maximilian Rohland. 2017. "Preserving Containers." In *Forschungsdaten managen*, edited by Jonas Kratzke and Vincent Heuveline, Heidelberg, 143–151. heiBOOKS. http://books.ub.uni-heidelberg.de/heibooks/catalog/book/285.

Rule, Adam, Amanda Birmingham, Cristal Zuniga, Ilkay Altintas, Shih-Cheng Huang, Rob Knight, Niema Moshiri, et al. 2019. "Ten simple rules for writing and sharing computational analyses in Jupyter Notebooks." *PLOS Computational Biology* 15 (7): e1007007. https://doi.org/10.1371/journal.pcbi.1007007.

Sandve, Geir Kjetil, Anton Nekrutenko, James Taylor, and Eivind Hovig. 2013. "Ten Simple Rules for Reproducible Computational Research." *PLoS Computational Biology* 9 (10): e1003285. https://doi.org/10.1371/journal.pcbi.1003285.

Santana-Perez, Idafen, and María S. Pérez-Hernández. 2015. "Towards Reproducibility in Scientific Workflows: An Infrastructure-Based Approach." https://doi.org/10.1155/2015/243180.

Schönbrodt, Felix. 2019. "Training students for the Open Science future." *Nature Human Behaviour* 3 (10): 1031–1031. https://doi.org/10.1038/s41562-019-0726-z.

Shannon, Jerry, and Kyle Walker. 2018. "Opening GIScience: A process-based approach." *International Journal of Geographical Information Science* 32 (10): 1911–1926. https://doi.org/10.1080/13658816.2018.1464167.

Sidhu, Nanki, Edzer Pebesma, and Gilberto Câmara. 2018. "Using Google Earth Engine to detect land cover change: Singapore as a use case." *European Journal of Remote Sensing* 51 (1): 486–500. https://doi.org/10.1080/22797254.2018.1451782.

Singleton, Alex David, Seth Spielman, and Chris Brunsdon. 2016. "Establishing a framework for Open Geographic Information science." *International Journal of Geographical Information Science* 30 (8):

1507–1521. https://doi.org/10.1080/13658816.2015.1137579.
Spielman, Seth E., and Alex Singleton. 2015. "Studying Neighborhoods Using Uncertain Data from the American Community Survey: A Contextual Approach." *Annals of the Association of American Geographers* 105 (5): 1003–1025. https://doi.org/10.1080/00045608.2015.1052335.
Stark, Philip B. 2018. "Before reproducibility must come preproducibility." *Nature* 557: 613. https://doi.org/10.1038/d41586-018-05256-0.
Stodden, Victoria. 2009. "The Legal Framework for Reproducible Scientific Research: Licensing and Copyright." *Computing in Science & Engineering* 11 (1): 35–40. https://doi.org/10.1109/MCSE.2009.19.
Stodden, Victoria, and Sheila Miguez. 2014. "Best Practices for Computational Science: Software Infrastructure and Environments for Reproducible and Extensible Research." *Journal of Open Research Software* 2 (1): e21. https://doi.org/10.5334/jors.ay.
Stodden, Victoria, Jennifer Seiler, and Zhaokun Ma. 2018. "An empirical analysis of journal policy effectiveness for computational reproducibility." *Proceedings of the National Academy of Sciences* 115 (11): 2584–2589. https://doi.org/10.1073/pnas.1708290115.
Sui, Daniel, and Peter Kedron. 2020. "Reproducibility and Replicability in the Context of the Contested Identities of Geography." *Annals of the Association of American Geographers* (In print). https://doi.org/10.1080/24694452.2020.1806024.
Sui, Daniel, and Shih-Lung Shaw. 2018. "Outlook and Next Steps: From Human Dynamics to Smart and Connected Communities." In *Human Dynamics Research in Smart and Connected Communities*, edited by Shih-Lung Shaw and Daniel Sui, Human Dynamics in Smart Cities, 235–245. Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-73247-3_13.
Tennant, Jonathan P., Harry Crane, Tom Crick, Jacinto Davila, Asura Enkhbayar, Johanna Havemann, Bianca Kramer, et al. 2019. "Ten Hot Topics around Scholarly Publishing." *Publications* 7 (2): 34. https://doi.org/10.3390/publications7020034.
The Turing Way Community, Becky Arnold, Louise Bowler, Sarah Gibson, Patricia Herterich, Rosie Higman, Anna Krystalli, Alexander Morley, Martin O'Reilly, and Kirstie Whitaker. 2019. "The Turing Way: A Handbook for Reproducible Data Science." Web. https://doi.org/10.5281/zenodo.3233986.
Vandewalle, Patrick, Jelena Kovacevic, and Martin Vetterli. 2009. "Reproducible research in signal processing." *IEEE Signal Processing Magazine* 26 (3): 37–47. https://doi.org/10.1109/MSP.2009.932122.
Verstegen, Judith A. 2019. *JudithVerstegen/PLUC_Mozambique: First release of PLUC for Mozambique (Version v1.0.0)*. Web: Zenodo. https://doi.org/10.5281/zenodo.3519987.
Verstegen, Judith A., Derek Karssenberg, Floor van der Hilst, and André Faaij. 2012. "Spatio-temporal uncertainty in Spatial Decision Support Systems: A case study of changing land availability for bioenergy crops in Mozambique." *Computers, Environment and Urban Systems* 36 (1): 30–42. https://doi.org/10.1016/j.compenvurbsys.2011.08.003.
Šimko, Tibor, Lukas Heinrich, Harri Hirvonsalo, Dinos Kousidis, and Diego Rodríguez. 2019. "REANA: A System for Reusable Research Data Analyses." *EPJ Web of Conferences* 214: 06034. https://doi.org/10.1051/epjconf/201921406034.
Wainwright, Joel. 2020. "Is Critical Human Geography Research Replicable?" *Annals of the Association of American Geographers* (In print). https://doi.org/10.1080/24694452.2020.1806025.
Waters, Nigel. 2020. "Motivations and Methods for Replication in Geography: Working with Data Streams." *Annals of the Association of American Geographers* (In print). https://doi.org/10.1080/24694452.2020.1806027.
Wilkinson, Mark D., Michel Dumontier, IJsbrand Jan Aalbersberg, Gabrielle Appleton, Myles Axton, Arie Baak, Niklas Blomberg, et al. 2016. "The FAIR Guiding Principles for scientific data management and stewardship." *Scientific Data* 3: 160018. https://doi.org/10.1038/sdata.2016.18.
Wilson, John P., and Peter A. Burrough. 1999. "Dynamic Modeling, Geostatistics, and Fuzzy Classificaiton: New Sneakers for a New Geography?" *Annals of the Association of American Geographers* 89 (4): 736–746. https://doi.org/10.1111/0004-5608.00173.
Wilson, John P., Kevin Butler, Song Gao, Yingje Hu, Wenwen Li, and Dawn J. Wright. 2020. "A Five-Star Guide for Achieving Replicability and Reproducibility When Working with GIS Software and Algorithms." *Annals of the Association of American Geographers* (In print). https://doi.org/10.1080/24694452.2020.1806026.
Xie, Yihui. 2015. *Dynamic Documents with R and knitr, Second Edition.* CRC Press.