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The importance of open science for biological assessment

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Abstract:	Open science principles that seek to democratize science can effectively bridge the gap between researchers and environmental managers. However, widespread adoption has yet to gain traction for the development and application of bioassessment products. At the core of this philosophy is the concept that research should be reproducible and transparent, in addition to having long-term value through effective data preservation and sharing. In this paper, we review core open science concepts that have recently been adopted in the ecological sciences and emphasize how adoption can benefit the field of bioassessment for both prescriptive condition assessments and proactive applications that inform environmental management. An example from the state of California demonstrates effective adoption of open science principles through data stewardship, reproducible research, and engagement of stakeholders with multimedia applications. We also discuss technical, sociocultural, and institutional challenges for adopting open science, including practical approaches for overcoming these hurdles in bioassessment applications.
Response to Reviewers:	Please see cover letter.

SOUTHERN CALIFORNIA COASTAL WATER RESEARCH PROJECT
A Public Agency for Environmental Research

August 21st, 2019

Dr. Charles Hawkins
Chief Editor
Freshwater Science

I am pleased to resubmit our manuscript, "The importance of open science for biological assessment," to be considered as a perspectives article in Freshwater Science.

We greatly appreciate the comments provided by our reviewers and the associate editor. We have fully considered these comments in our revision of the manuscript and our line-by-line responses to each comment are provided below. In short, we have clarified our use and consistency of terminology, shortened the content by several pages including reduced repetition of ideas, and expanded on points raised by both reviewers in the "limitations and opportunities" section. Detailed responses to reviewer comments were also provided for instances where we thought explanations were needed but additions to the text were unnecessary.

Our organization agrees to submit payment for page charges if the paper is published. We are confident that readers of FWS will find this manuscript informative and again appreciate the opportunity to publish our work in this venue.

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On behalf of my co-authors:

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Response to reviewer comments on the manuscript "The importance of open science for biological assessment", by M. W. Beck, C. O'Hara, J. Stewart Lowndes, R. D. Mazor, S. T. Theroux, D. J. Gillett, B. Lane, and G. Gearheart.

We thank the associate editor and both reviewers for providing detailed and thoughtful comments on our manuscript. Our responses to these comments are below.

Associate editor comments:

I believe the manuscript addresses an extremely important topic that should be relevant to virtually all Freshwater Science readers. Overall, the arguments are convincing and the writing is adequate. Both reviewers and I have provided numerous suggestions that should greatly improve the manuscript. Reviewer 2 is a state-level bioassessment expert, and provides several additional questions/issues that, if addressed, could make your paper more appealing to that audience. Consider their suggestions—although some are a bit off topic. Reviewer 3 is from academia and provides many excellent suggestions to improve the flow and simplify your message. They suggest a change in the tone of your manuscript—to one that is less pontificating. I didn't get the same impression—but largely because open science has been drilled into my head as a federal government scientist. I provide below a few general suggestions, followed by detailed notes as I read through the manuscript.

Terminology is inconsistent. For example, "methods," "tools," "products," etc. are used interchangeably and it leads to confusion. There were sentences where "tool" made more sense but you used "method" instead. If you want to keep using all these terms, you need to define them up front. Otherwise, use a consistent term that encompasses all these aspects of bioassessment.
We have revised the text for consistency in terminology. In short, the text now refers only to "bioassessment products" and "open science tools", with definitions for both provided in the introduction. Please see our specific response to your comment on Line 80.

Reviewer 2 was troubled by redundancy throughout the manuscript. On the one hand, redundancy is helpful when you're trying to, in essence, teach readers a new thing. But you also run the risk of an excessively long manuscript, and annoying readers who feel like they're reading the same things over and over. I've indicated in my specific comments where you might trim some material so that redundancy is less glaring (as did Reviewer 3). But I also urge you to take a close look at how you could minimize redundancy throughout the manuscript. Another idea to consider is that you seem to discuss the concepts of, say, open data in the "Principles" section, but then repeat a lot of the same material in the "Bioassessment" section. I suggest carefully wording each section so there is less redundant information.
Our repetitive approach was somewhat intentional in order to emphasize key concepts, as you suggested. However, the manuscript is quite long, and we agree it can be shortened in some instances while still communicating critical ideas. We have removed portions of the text where you and reviewer three have commented specifically. As one example, the content from the section "Open science in practice" that described the SCAPE tool was shortened from ten paragraphs to four. See our responses below for specifics. In total, these omissions have shortened the manuscript by approximately nine pages (double-spaced).

I've also indicated sections in the document that stray from the main topic (e.g., discussion of thresholds), and that are burdened by excessive detail (SCAPE tool description). These sections should be removed and / or dramatically trimmed.

AE SPECIFIC COMMENTS

Line 50: Not sure how "methods" could be transformed into actionable information. I can envision results and tools being transformed.
Agreed, sentence was revised to "…that transform bioassessment products into actionable information."

Lines 59-62: This sentence is too complex and also unclear. Consider splitting and rewording to clarify. Do you mean that bioassessment tools are being used in a post hoc fashion rather than for protective/preventative purposes (e.g., anti-degradation)? OK, the sentences after this one provide clarity & examples. DELETE THIS sentence.
Sentence was deleted.

Line 67: Unclear what you mean by "discoverability of existing products by other research teams…" I sort of know what you're getting at, but the sentence needs to be more clear. I think you're saying that more discoverability and open sharing of bioassessment data, methods, and tools among researchers is essential to…
Paragraph was removed in response to comments from reviewer three.

Line 72: Have bioassessment tools really become "diagnostic?" To me, a diagnostic tool reveals WHY someone is sick. I don't think we're there yet with biological assessments. We do a good job of determining WHETHER a stream is impaired, but can you cite evidence that we've been able to develop tools that diagnose the potential causes?
Agreed, most indices do not provide this information and causal assessments could be used to identify specific stressors. I replaced "diagnostic" with "sensitive".

Line 80: You seem to be using bioassessment "products," "methods", and "tools" interchangeably. I think you need to define what these mean, or stick with a single general term.
We agree our use of different terms was inconsistent and confusing. We have chosen to use "products" for bioassessment and "tools" for open science. We feel this adds consistency of meaning and have included a brief description in the introduction to clarify each term. From the second paragraph: "In the United States, the CWA gives power to states, tribes, and territories for bioassessment development, where final products (i.e., assessment indices or other products that support biointegrity decisions) require federal approval…". From the final paragraph of the introduction: "Herein, open science "tools" describe best practices and specific applications that use an open philosophy to support applied science."

Line 87: Not sure what you mean by "…existing methods may not be discoverable beyond immediate research applications…" Are you referring to actual bioassessment tools such as an IBI for a region? Or are you referring to the actual methodology, which is typically "discovered" by reading the literature?
Sentence was revised to: "Moreover, existing indices may not be easily replicated beyond initial research applications…"

Lines 90-92: Here you focus on "methods," but I don't see how managers would be interested in choosing methods. It seems like that is a challenge for the scientists. Again, are you referring to tools or applications?
This sentence was revised based on the general comments above about consistency of terminology: "The abundance of available products can be a point of frustration for managers given a lack of guidance for choosing among alternatives, particularly as to how different assessment products relate to specific management, monitoring, or policy objectives (Dale and Beyeler 2001; Stein et al. 2009)."

Line 105: Publicly funded science is not unique to bioassessment, so I don't see why this sentence is relevant.
This was revised as our original intent was to highlight the link to public natural resources, not public-funding: "Legal and ethical precedents in bioassessment may also necessitate open data sharing given that environmental monitoring programs are often established to protect and maintain publicly-owned natural resources."

Lines 124-153: Nicely written!

Line 174: Most synthesis products are, in my opinion, GREATER than the sum of the individual datasets. The SUM, would be just a summary of the individual datasets. A synthesis implies taking the additional step of advancing the science.
Sentence was revised: "Collaborative publications have increased in the environmental sciences as research teams leverage open data to create synthesis products that allow novel insights from comparisons across multiple datasets"

Lines 202-258: This section should be reconsidered. In it, you provide an introduction to the sections that follow, but in so doing you discuss many of the ideas that will follow. So, when readers actually read the next section, they get the impression they've heard this before. I suggest dramatically reducing this section and dropping ideas and examples that you're going to flesh out in the subsequent section.
This section was shortened to retain only key ideas that support the introduction of the following sections. Lines 208-231 were removed – these lines described molecular advances in bioassessment, which are important but unnecessary to describe for our larger goals. Lines 245-258 have also been removed as they are almost entirely redundant with the following sections.

We have retained most of the content on lines 203-214 and 232-244 because it provides a good lead-in to the following sections by 1) describing the overall workflows in figure 2 (lines 203-214), and 2) clarifies that openness occurs on a continuum (lines 232-244). We feel that this material is not redundant and emphasizes key points to provide additional context in the following sections.

Line 286: This is an example of a redundant idea. You talked about this in Line 250.
Line 250 was removed.

Lines 352: Again, I get the feeling I've read this in previous paragraphs.
This line was removed.

Line 364: I'm not sure what you mean by " bioassessment translation" You describe it in the opening paragraph, but it still doesn't seem like the correct word choice. Why not "application" or "implementation?"
Agreed, "translation" is a bit loose and we've changed it to "bioassessment application" in the subsection title and other instances in the text. We also provide a clear definition of what this means in the opening paragraph: "Bioassessment application is the linkage of products between the research and management community, where links are enabled through open science tools that can deliver the products using a reproducible and accessible platform."

Line 390: You're using jargon (geometries, aesthetics) from Wickham here. The readers that you're trying to convince to use these types of tools will not understand these terms.
Replaced "geometries and aesthetics" with "instructions".

Lines 526-537: This paragraph seems to be straying off topic. Here, you're delving into the challenges of setting thresholds. Suggest dropping paragraph.
Paragraph was removed.

Lines 538-552: Same as last paragraph. You're getting into one technical challenge of bioassessments that is a good topic for another paper, but seems tangential to this one. Drop paragraph.
Paragraph was removed.

Lines 570-639: Pointing to this tool is a good idea, but you go into WAY too much detail about its development. Reduce these paragraphs by 90% by simply stating the problem that the tool was developed solve, that it was developed using open science principles (no need for detail here), and how it has been received. Cite your forthcoming paper for the details.
Lines 553 – 639 were shortened substantially to highlight the key points of SCAPE that are relevant for understanding open science applications in a practical example. This reduced the content down to two paragraphs, one describing the problem that SCAPE addresses and another that describes the open science components. Many details for the latter were minimized to reduce redundancy with previous sections.

Reviewer 2 comments:

This paper is ambitious in scope. It includes a philosophy, a catalog of tools, and a realized example of the philosophy and tools in action. The open science paradigm is a bold proposal that is certainly worthy of debate in the scientific community.

The manuscript is well written, well organized, includes sound science, and communicates concepts clearly. However, it has some gaps, particularly in the area of the underlying assumptions of the open science philosophy and its possible real world implications. Because the novelty of this paper is philosophical rather than technical per se, and the authors are calling for a philosophical paradigm shift, these areas need to be addressed.
We appreciate the insightful comments and suggestions provided below. We have made every attempt to address your concerns either through revisions and additions to the text or responded directly herein where we felt elaboration was needed. Please see the detailed responses below.

It is this reviewer's opinion that the manuscript would be more defensible and better received in the wider community if gaps and potential concerns are addressed. To wit:

1. To some, the "democratization of [any professional field]" can be viewed, alternatively, as a "shackling of the [professional]" to the lowest common denominator. In the case of a scientist, for example,
a. When the scientist is required to work in a fishbowl and defend (or at least "sell") every step of his or her work, the process becomes a beauty contest or a sales competition, rather than a scientific pursuit. The very reason we have civil service is to provide a measure of stability and impartiality, and insulate professionals to some degree from political biases and public whims.
b. Subjecting the processes (rather than merely the inputs and outputs) of a scientist's work to the political will of nonprofessionals denies them their professionalism and erodes the very idea of what it means to be an educated, knowledgeable specialist. The silent corollary is that every aspect of a professional's work should be made publicly understandable, so that public judgment can replace professional judgment in the course of work. Yet there is a reason that our society is built on Division of Labor - it allows professionals the luxury of mastering special knowledge and understanding that not

everyone else has. This specialization advances the society as a whole.
c. An example may be illustrative. My doctor and I are user (manager) and consumer (stakeholder) of what the pharmacist dispenses to me based on a prescription, and we both have high stakes in the quality of the pharmaceutical products. We may express our political, personal, or professional will regarding what drugs are brought to market, and we may express our (dis)satisfaction with the end results. However, we have no expectation that we be directly involved in the pharmaceutical development process. Rather, we trust that the work is peer reviewed, tested, and judged by the appropriate professionals whose special knowledge is appropriate to the task.
You provide valid counter-arguments to the openness that we advocate for in our paper. My interpretation of your comments is that 1) openness has the potential of degrading scientific integrity by allowing potentially unqualified individuals a greater say in the process, and 2) increasing openness can indirectly force scientists to pursue projects with wider appeal (or less controversial) that may not have as much scientific rigor as less "charismatic" products. So, your overall concern is that openness can degrade the quality of science.

I think these are valid concerns and our current section on "limitations and opportunities" provides commentary on some of these issues. For example, line 685 in the previous draft stated that "research teams using transparent workflows could expose themselves to increased criticism by their peers and the public." Moreover, line 677 states a common argument against open science in cases when data are sensitive or otherwise proprietary. We believe that specific situations may preclude the use of open science tools and a researcher should be aware of these concerns so they can assess the costs/benefits of openness – which was our intent of including this section. However, we stress that the current literature includes many examples of how open science can improve the quality of the scientific product (e.g., Hampton et al. 2015; Ihle et al. 2017; Lowndes et al. 2017). Other examples have demonstrated that a lack of inclusion, either through "siloing" of research processes (as can be common in academia; Mitchell 2005; Liu et al. 2008) or exclusion of stakeholders, can seriously hinder the utility of an applied product. Thus, there is an increasing amount of evidence that openness has net positive benefits for scientific integrity. We draw on some of your concerns in our response to point three below.

2. The authors quickly dismiss the idea of any government agency or personal "ownership" of the data, methods, work processes, and work products of government scientists. They also characterize bioassessment as different from other science in that it is meant not to stand alone (for example, simply to determine whether a waterbody is healthy and supporting aquatic life), but to serve the aims of managers. The unspoken corollary to this view is that bioassessment scientists are not "real" scientists, but rather mere functionaries. I would caution the authors to be careful here. On a regular basis, many government employees design protocols, methods, and studies, and then generate data, tools, reports, and publications that meet or exceed the standards of academic work. Moreover, their work products are not biased by a "positive results" publication imperative, and their data have the added advantage of residing in an institutional repository where they will be retrievable for generations, or as long as the internet infrastructure is intact.
We disagree that an unspoken corollary of this work is that "bioassessment scientists are mere functionaries". Rather, our intent was to make a distinction between more traditional fields of science (e.g., theoretical disciplines) vs those described as applied science. Bioassessment is one of many fields in the latter category that provide valuable knowledge and services, often with the objective of protecting public goods and resources. One of our statements in the introduction clarifies this point: "The explicit link to environmental management distinguishes bioassessment from basic ecological research. Although bioassessment can and has been used to inform basic research, its intended use is to inform the protection and restoration of ecological integrity." I do not think most bioassessment scientists would disagree with these statements. Linking bioassessment to its applied components is a

central piece of this paper, where this link can be greatly strengthened through the use of open science tools. De-emphasizing this link would of course weaken our arguments.

We also disagree with the idea that government research is somehow less valid than research produced in other institutional frameworks (e.g., academia). Nowhere in the text did we make this claim, nor do we feel is it implied by our statements that "ownership" of data by an institution has systematically lowered the quality of science produced through government research. Our discussion of open data as a fundamental component of open science was meant to highlight how openness can facilitate application, particularly in a field like bioassessment where the products often have a clear intended use. Many government agencies are seeing the value of open data (e.g., AB1755 in California), not because science was internally hindered from closed data, but because science can have a greater impact through openness. Anecdotally, AB1755 has encouraged more government data stewardship, including the use of data in government programs and services aimed at addressing underlying water quality programs. It is this openness and stewardship that encourages collaboration.

3. We live in an era in which many loud political voices devalue science and even denigrate and attack it. Many stakeholders are, in fact, critics who have particular self interested motives and will find any chink in the armor of those who seek to protect natural resources. The authors seem to tacitly assume that opening up the workspaces of professional scientists to the public and to policymakers will not make our natural resources more vulnerable, but rather will restore public trust in our work and our institutions. This belief seems, at best, naïve. It would be helpful if the authors could explain the mechanism by which the shrill enemies of science would become allies, if only they could impose their will on the process - and how this would not erode the foundations of impartiality upon which the scientific method is founded.
Our previous paragraph on line 676 spoke to these concerns. In particular, lines 688-691 stated the following: "An argument made throughout this paper is that regulatory, management, and stakeholder groups that will both use and be affected by bioassessment products should be integral contributors to the development process. An open science bioassessment process welcomes criticism and feedback as a natural part of development that will facilitate adoption by ensuring the product meets the needs of all parties."

To better address your concerns, we have elaborated on these ideas and included the following text in "limitations and opportunities" section:

"Feedback and criticism are fundamental and natural parts of the scientific process. Scientists receive feedback at many stages in the conventional scientific workflow (e.g., internal review, peer-review, presentations at conferences). Potentially new and challenging avenues for feedback are created in an open workflow. A concern is that openness can provide a platform for antagonistic or even hostile views, which could alter or degrade the scientific product (Landman and Glantz 2009, Lewandowsky and Bishop 2016). However, opportunities for addressing alternative viewpoints are critical to the open process of creating applied products, even if some voices are politically charged. This is especially true in bioassessment where finished products that could be adopted in regulation are often heavily scrutinized. It is in the interest of applied scientists to hear the concerns of all parties during the development phase. This is not to provide an avenue to erode the integrity or objectives of the science, but to enable full knowledge of the very real barriers to adoption that exist when science is applied in regulation. Openness that invites all voices to participate is a much more agreeable path to consensus than producing the science in isolation of those that it affects (Pohjola and Tuomisto 2011). Ultimately, these products are developed to improve the environment as a public resource and the ideals promoted by an open science process directly align with these goals."

4. The authors have demonstrated clarity of thought and expression. It is very good that they draw a clear distinction between "open data" and "open tools," versus "open science." It is true that government could do somewhat better with "open tools," though more and more government scientists are converting tools to the R programming environment and contributing packages to CRAN, for example. However, the authors do a significant disservice to government agencies by failing to catalog or even mention the extensive effort that has been invested in ensuring both the quality and availability of data. Some of these include the following:
a. Data sharing and data comparability are a centerpiece of federal water monitoring programs, under ACWI and the NWQMC. https://acwi.gov/methods/pubs/over_pubs/valcomp_fs.pdf
b. Federal agencies are already committed to open data. USGS (which operates NWIS and BIODATA) and USEPA (which operates WQX/STORET) collaborate via the Water Quality Portal and the Internet of Water, as well as maintenance of the National Hydrography Dataset and its derivative products, in order to make high quality data available to the scientific community and the general public.
c. State and Tribal data collected under EPA funding is required to be uploaded to STORET/WQX.
d. (Side note - the SCAPE model described in this article appears to have been built on StreamCat, an EPA produced, publicly available geospatial dataset. The SCAPE website clearly credits StreamCat; this manuscript probably should as well.)
We agree that many of these national-level products that encourage quality and comparability of data were not mentioned.

We have added content to describe these products (line 704): "Many national-level data products already exist that embrace openness to invest in the quality and availability of data (e.g., National Wata Quality Monitoring Council initiatives, US Geological Survey products through NWIS and BioData, US Environmental Protection Agency through STORET/WQX)."

Citations for StreamCat and NHD-Plus were also added to line 564: "Using the National Hydrography Dataset (NHD-Plus; McKay et al. 2012) and watershed predictors (StreamCat; Hill et al. 2016), the model classifies stream segments as biologically "constrained" or "unconstrained" by landscape alteration."

5. Although some thresholds are predictive (for example, 30% impermeable surface), landscape based watershed models show relatively poor correlation to macroinvertebrate assemblage quality, whereas instream habitat characteristics, certain water quality chemistry measures, and riparian corridor characteristics have better predictive value. The authors of the SCAPE model undoubtedly understand this as well as the nuances of natural stream classes, metric development, etc. Is it fair to ask, however, whether even the most thoughtfully designed tool can be misued by someone who does not understand it? Is it possible that the SCAPE tool could lead the novice/layperson user to conclusions or decisions that are distorted or entirely inappropriate? It is a relevant question.
This comment addresses one of the main concerns we had developing the SCAPE tool – we did not develop the tool to "write-off" sites that are "beyond hope", rather our intent was to provide a prioritization tool to identify sites where management actions could have intended outcomes. Prior to SCAPE, managers had no context for identifying biointegrity priorities in developed landscapes. In other words, prior to SCAPE, all urban sites were "bad", but now we can see that not all sites are created equal and there are indeed opportunities at locations where scores were otherwise not as expected. Our intent was to allow managers to use this information to prioritize among the "bad", as opposed to just doing nothing.

We developed SCAPE through close interaction with stakeholders (box 1 in figure 4) and with members of the state water board to communicate our intended use of the model results. Our open process made

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these interactions possible and in doing so we feel there is greater likelihood that SCAPE will be used as intended. Of course some might abuse products, which has certainly happened in the past, but every effort has been made to communicate intent with those that make decisions that will affect how SCAPE could be implemented. We encourage you to review our full manuscript on SCAPE in FWS when it becomes available (provisionally accepted as of now, pending Editor-in-Chief final review).

That being said, much of the section referring to SCAPE has been shortened and only relevant text has been retained. This discussion applies more to our forthcoming article and less-so about this paper.

6. This manuscript focuses on bioassessment data in particular, but it gives scant attention to the particularly thorny nature of biological data. The authors cite Cao and Hawkins 2011, but they do so in a general discussion of "duplicated effort" and "lack of coordination in the monitoring community." The same paper, in fact, is a good review of the particular difficulties of biological data. This manuscript would benefit from a short discussion of the unique characteristics and problems of biological data that set it apart from other data types, such as nested hierarchy, changing taxonomy, ambiguous taxa, the importance of ancillary information such as ecological and toxicological data, etc. Other papers in this vein are Cuffney et al 2007 (JNABS 26:286), Lenat & Resh 2001 (JNABS 20:287), Chessman et al 2007 (JNABS 26:546) and Stribling 2011 (Chapter 4 in the book "Modern Approaches to Quality Control.")
The following was added to the beginning of the section "curating bioassessment data" to provide some context on specific challenges with these data: "After project goals are established, the research team identifies requirements and sources of data that need to be synthesized to meet the research needs. Bioassessment data, or more generally, biological data obtained from field sampling have a unique set of challenges that require added vigilance in data stewardship (Cao and Hawkins 2011). Taxonomic resolution requires a tradeoff between specificity with added cost (Lenat and Resh 2001, Chessman et al. 2007) and names change regularly requiring updates to standard taxonomic effort (STE) tables that are critical for many biological indices. Unidentified or ambiguous individuals or taxa must also be explicitly treated in analysis workflows (Cuffney et al. 2007), e.g., are they treated as missing values or are they substituted with coarser taxonomic designations? Environmental data that describe physical or chemical conditions are also critical to support development of an assessment index, as well as understanding potential stressors or background condition that could influence biological condition."

Reviewer 3 comments:

Summary: In this article the authors outline the ways in which open science principles and technologies can be applied to bioassessment to better link science and management. This is done by summarizing open science core concepts, and new and emerging tools for application by researchers and managers. It is further illustrated by describing recent development of a bioassessment products using an open science approach.
We greatly appreciate your detailed comments on our manuscript and have made every effort to address them through revision or direct comments herein.

General Notes: The topic is important, and the article is generally well written. The primary drawbacks were that it seems much longer than is necessary, is repetitive, and does not always make clear how open science approaches will advance bioassessment. It can be "preachy" at times, assuming that end users are very reluctant to adopt these approaches instead of (as I suspect) mainly overburdened and lacking appropriate support. For example, most research projects have 1-2 years of funding; management agencies and their priorities are funded on 2-4 year legislative cycles. In this context, producing a grey literature or peer-reviewed article may be the only/most viable option for communication.

Your comment suggests the tone of the writing be modified. As noted above in our response to the AE, our writing style was purposeful and included repetition to convince others that open science is a valuable investment of time and resources. Given your comments and those from the AE, we realize this writing style was not very effective. In the revisions throughout, much of the repetitive content has been reduced. We feel this has improved the tone significantly. Also, please see our response to providing "practical solutions" in the "Limitations and opportunities" section.

In this same vein, who is the target audience(s) - is this article intended to convince funding sponsors and/or legislators holding the purse strings? State bioassessment program mangers? Academic researchers? In my experience, the hurdles may differ among groups. For example, academic researchers may be in a better position to adopt new tools, but have less access to manager/stakeholder input or ability to sustain an interactive website over time. Conversely, state agencies may be in a position to sustain a website over time (maybe!), but have less bandwidth to explore and learn new tools given their management mandates. Collaborations may be an important and critical way to overcome these kinds of institutional limitations for open science.
The appropriate audience for this manuscript was an early point of discussion among the co-authors. It was our hope that the article would have broad appeal to many in the bioassessment community. For example, we provide detailed descriptions of specific open science tools that the research community can leverage, while we also discuss the benefits of open science from an institutional perspective. We admit that the article is slightly balanced towards the research community (i.e., our repeated use of the term "research team"), but we also wanted to write in an appealing way for managers or funding agencies that use or support research, i.e., investments in open science by these parties will likely have long-term returns. We have clarified this intent in the introduction (line 113): "As such, this paper is written primarily for the research team that develops bioassessment products, but we also write for the funders and users (e.g., regulators and managers) of these products to emphasize the value of investing in open science for the protection of public resources."

The article would be stronger if it were shorter and focused less on convincing the reader, and more on encouraging/hand-holding by 1) demonstrating the benefits 2) frankly acknowledging challenges, and 3) presenting open science as a series of "components" that facilitate a more transparent, repeatable, and iterative/engaging process (vs. assessment itself being "open" or "closed').
We hope that our revisions to shorten some of the sections have strengthened our narrative.

The specific comments below all stem from the general notes.

Introduction: Is too long. It has good information, but makes the point in multiple ways that bioassessment is uniquely embedded in legislation/management action and could benefit from adoption of open science. For example, the exact words "hundreds of assessment methods" appear in the 1st and 3rd paragraphs, and similar points appear throughout. The challenges presented are accurate, but I have a hard time seeing how adopting open science will necessarily meet all of them. For example, abundance of methods and lack of guidance (Lines 90-93) is a problem, but having these same methods available more openly wouldn't necessarily provide guidance on which ones are most appropriate. Also, the way that challenges are interspersed with how open science provides solutions are muddled and difficult to follow. For example, "Biological indices are typically used to develop post-hoc diagnoses to trigger remediation or restoration actions, or to serve as early warning indicators of environmental change" (Lines 63-64) - but then "discoverability" (Line 67) is presented as the solution to this challenge.
Changes to the introduction are as follows:

- *The entire second paragraph was removed (lines 52-70) as most of the content was repetitive.*
- *Removed redundant language, e.g., "hundreds of assessment methods".*

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- *Removed any direct statements that are unsubstantiated, e.g., discoverability will provide guidance on choosing a method. Although we agree that having methods more open does not necessarily help with choosing a bioassessment product, it does directly address repetition by preventing others from reinventing the wheel.*
- *First and third (now first and second) paragraphs were revised in accordance with the flow of ideas outlined in the responses below.*

I think a better approach is to briefly summarize the benefits of open science (either in bioassessment or other fields) and present it as one way to help address the science-management gap that is currently identified in bioassessment, without trying to map out how it will exactly address very specific challenges.
Please see comments above about our restructuring of the introduction. The flow of ideas in the introduction is structured around 1) bioassessment as an applied tool (paragraph 1), 2) implementation challenges (paragraph 2), 3) open science to address these challenges (paragraph 3), and 4) goals/objectives paragraph.

Line 56-58: What is "imbalance" here? Seems to need a citation too
This sentence was removed.

Lines 108-123: Repeats much of the abstract. Recommend writing this as objectives, and - more importantly - identifying your audience(s) and what they should get from reading the article.
This paragraph was shortened to reduce redundancy with the abstract. We have also explicitly indicated the intended audience for this paper. Please see our response above.

Lines 97-103. I wouldn't call out that bioassessment has or has not embraced open science compared to other disciplines; it's very subjective - and constraints of time, funding, and expertise are the likely culprits. Sustaining management attention can be a big hurdle too for agencies. However, there is a case that bioassessment could benefit somewhat uniquely from these tools, due to the nature of being embedded in legislative mandate/public interest (requiring transparency), being a relatively new mandate/concept (requiring ongoing development), and the need for each state to conduct and report on monitoring (requiring replicability).
Sentence was revised: "Open science principles that democratize all aspects of the scientific method can help meet these needs and there is a unique opportunity in bioassessment to leverage openness to support public resources."

Lines 125-153. I don't think it's necessary to elaborate on the distinction between "conventional" and "open-science" approaches - managers and researchers are pretty aware of the limitations of current approaches; besides it's already covered in the Introduction. Defining what you mean by open science here should be sufficient, without calling out everything that's wrong with non-open science.
We feel this section provides a good introduction to the issues that open science remedies and we have retained the content (also see AE comments for this same section). Further, the revisions to the introduction have reduced any redundancies with this section.

Line 154-201: Why is open data not part of the open science principles section? This section also seems very long to make a point that is widely accepted (although one that can be difficult to implement and - more importantly - sustain)
We want to distinguish open data as a unique component of open science, so we retain the content in its own section. However, we have shortened the content to reduce redundancy and retain only the main points.

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Sections "Applying open science principles to bioassessment" and "Conventional bioassessment" are making the same points, but from an inverted perspective. Example: Lines 255-256 is about accessible data and lines 272-273 are about inaccessible data. Also, lines 261-263 state: "A typical workflow for developing a bioassessment product is not entirely dissimilar from a conventional scientific process" - exactly. So it's not necessary to elaborate on the standard process, it's the one everyone knows. These two sections also repeat the same challenges raised elsewhere.
Agreed that there was redundancy between these sections. We have revised the "Applying open science principles to bioassessment section" to serve only as an introduction to the following sections. Also, please see our response to the AE on the same topic (i.e., response to comments on lines 202-258.

Lines 296-297: they are uncommon in all disciplines - it doesn't seem helpful to call out the bioassessment community
This sentence was removed based on revisions to this section.

Lines 309-314: This is fairly redundant with Figure 4 (but doesn't reference it). Also is related to the sections after, but not aligned with them.
We have removed figure 4.

Lines 309-492: (Related to above) Coming up with a more streamlined way to refer to the recommended process will help organize the paper, avoid redundancy, and help readers follow along. In other words, I'm not sure what the intended organization is here and in the following sections - is it organized by process or by tools? Make use of the tables and figures whenever possible instead of walking readers through text-based descriptions of tools/packages. Also, I would probably avoid sticking in more justifications for open science approaches (e.g., lines 348-351) in these sections, since (hopefully) the reader has already bought in to the "why" at this point.
We have shortened and streamlined these sections to improve organization. Specifically, we have removed our example about the "conventional workflow" and consolidated figures and tables where appropriate. We have also specifically removed lines 348-351. Please see our responses to the other comments below for additional explanation of changes.

Lines 364-492: This section is too long, and walking readers through Table 2. If needed, expand Table 2 with some additional details or columns (e.g., example applications, which bioassessment steps it will help with) and dramatically cut down the text.
This section was reduced by nearly two pages.

Lines 459-468. Suggesting readers can start developing R packages for bioassessment is an off-putting stretch/tangent - if they are able to develop R packages, then they are already experienced in using these tools.
Our intent of this paragraph was to highlight the benefits of compartmentalizing a bioassessment product in an R package. We have modified the language to highlight the benefits, rather than suggesting that readers actively consider developing their own packages. This speaks to our intended audience for this paper, as noted above. For example, a manager reading this paper might read about the benefits of developing R packages and consider hiring or investing in someone with experience in this area to provide these services.

Line 493: Suggest subtitle "Open Science in Practice: The SCAPE Project". In this section, be sure to refine and present information that is relevant to open science and/or is not redundant with previous sections. For example, lines 526-537 rehash challenges and the science-management disconnect. Similarly, struggling to see how lines 538-552 relate to open science.

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Subtitle was changed as suggested. Much of this section was also reduced following recommendations herein and from the AE to reduce redundancy. In total, the content was reduced from ten paragraphs down to four.

Lines 588-631: I refer to this later (Figure 4), but this section is essentially a repackaging of Table 2 and Figure 3. Recommend cutting this and/or finding ways to integrate anything really essential or new into other sections.
Please see our response to the previous comment.

Section "Limitations and Opportunities". This is an important section, and the abstract states: "We also discuss technical, sociocultural, and institutional challenges for adopting open science, including practical approaches for overcoming these hurdles in bioassessment applications.". But I didn't find many practical suggestions for overcoming these hurdles in this section. For example, "Many scientists feel they cannot prioritize learning new skills given existing demands on their time" (648-649) and "requires a research team to stay abreast of new technologies as they are developed" (652-653)are big hurdles that won't be overcome by a better appreciation of the benefits of open science. Many of these hurdles are based in overarching constraints on the way science and management are funded and sustained (at the whim of short-term funding and even political cycles). My reading of this section is that it goes after the low-hanging fruit (e.g., scientific culture being closed to new ideas) instead of offering suggestions to counter the more intrinsic hurdles of lack of sustained funding, personnel, and expertise to develop open science models. I think focusing on suggestions that help overcome these types of hurdles will be better received and more reflective of the current challenges faced by research and management groups.
Your comment speaks to the core challenge in adopting open science tools, in that there is no easy or simple remedy to ease adoption. Our intent with this section was to highlight some of the main reasons why open science is not more widespread to, at the very least, allow readers to think about their own challenges as a starting point to adoption. Perhaps we were over-zealous in claiming that there are simple and "practical" solutions, but we firmly believe that some of the approaches we have described are the most effective (and practical) ways to promote adoption. In particular, lines 655-675 focus on teaching and creating communities of practice as a powerful approach to overcoming many of the hurdles we describe. Moreover, our broader intent with this paper was to emphasize the value that open science can have and to convince our readers that learning new tools is a valuable use of time (considering other demands).

Along these lines, we have added content to provide some more practical solutions (starting on line 675):

"…This also encourages the development of a community of practice that shares and learns together to navigate the collection of existing and developing open science tools. Champions of open science should also be vocal proponents that spread awareness of the value of open science tools, particularly to those that make decisions on project resources. Department heads or administrative leaders may not be aware of the value of investing in open science, particularly if the consequences of not doing so are externalized in indirect costs that are not budgeted. A change in mindset may be needed where open science is viewed as a core tool that is critical to maintaining relevance of a research program in the future (Hampton et al. 2017).

Many scientists feel they cannot prioritize learning new skills given existing demands on their time, particularly if the benefits of these approaches, such as the value for the research team of sharing their data, are not apparent or immediate. Short-term funding and even political cycles can disincentivize scientists from spending time on anything but contractually obligated deliverables, which as noted *above, may not effectively apply science in decision-making. This is an acute concern for early career scientists that have higher demands on establishing reputation and credentials, where investments in open science may be seen as detracting from progress (Allen and Mehler 2019). As an alternative, a practical solution is to actively encourage the investment in open science within the research team or lab, as opposed to placing the burden on the individual as an isolated researcher (i.e., team science, Cheruvelil and Soranno 2018). Laboratory or department heads should allow and encourage research staff to invest time in learning new skills and exploring new ideas, even if this does not immediately benefit the latest project. Over time, small investments in developing new skills will have long-term payoffs, particularly if a growing skillset among the research team encourages networking and peer instruction (Lowndes et al. 2017, Allen and Mehler 2019). Developing an environment where open science tools are highly valued and encouraged may also increase job satisfaction and benefit recruitment and retention if researchers are allowed the space and time to develop skills beyond the current project."*

Table and Figures

Figure 2. The "a" section detracts from this figure. I can think of many "conventional" assessments that incorporate some aspect(s) of an open science approach, but fall short of incorporating all aspects of it, due to lack of time/expertise/money etc. This figure would be better presented as "Idealized or potential components of bioassessment based on open science principles" to encourage adoption of different components - piecemeal if needed - vs. an all-or-nothing buyin.
We removed the top "conventional" subfigure to reflect the changes that were made to the text

Figure 4. This type of information is already presented in Table 2 and the text (and to some extent the workflow figure previous) - the large graphical representation seems unnecessary. Some information could be added to Table 2 if needed to replace this (i.e., more explicit explanations or examples of R package applications).
This figure was removed. We have added information in the SCAPE section to supplement any missing information (e.g., links to examples that are specific to SCAPE).

Running head: Open science for biological assessment

The importance of open science for biological assessment

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Abstract

Open science principles that seek to democratize science can effectively bridge the gap between researchers and environmental managers. However, widespread adoption has yet to gain traction for the development and application of bioassessment products. At the core of this philosophy is the concept that research should be reproducible and transparent, in addition to having long-term value through effective data preservation and sharing. In this paper, we review core open science concepts that have recently been adopted in the ecological sciences and emphasize how adoption can benefit the field of bioassessment for both prescriptive condition assessments and proactive applications that inform environmental management. An example from the state of California demonstrates effective adoption of open science principles through data stewardship, reproducible research, and engagement of stakeholders with multimedia applications. We also discuss technical, sociocultural, and institutional challenges for adopting open science, including practical approaches for overcoming these hurdles in bioassessment applications.

Introduction

Bioassessment is an essential element of aquatic monitoring programs and helps to establish a foundation of decisions for managing the ecological integrity of environmental resources. Legal mandates to assess biological condition have set a precedent for developing bioassessment products in the United States (Clean Water Act, CWA), Canada (Canada Waters Act), and Europe (Water Framework Directive). Decades of research to meet these mandates have supported the development of assessment indices for multiple assemblages with regional applications in streams, rivers, lakes, and marine environments (Karr et al. 1986, Kerans and

Karr 1994, Fore and Grafe 2002, Beck and Hatch 2009, Borja et al. 2009). Substantial technical advances have been made in predicting biological responses to environmental change (Hawkins et al. 2000a, 2000b), how these responses can be distinguished from natural environmental variation (Stoddard et al. 2006), and determining the impacts of these changes (Davies and Jackson 2006). The use of these products to support environmental management distinguishes bioassessment from basic ecological research. Although bioassessment can and has been used to inform basic research, its intended use is to inform the protection and restoration of ecological integrity. As such, environmental managers require additional tools that transform bioassessment products into actionable information.

Integrating bioassessment products into management or regulatory frameworks is a larger implementation challenge that continues to inhibit progress, despite the technological advances (Kuehne et al. 2017). Characterizing how an index could be used in practice to inform decisions and prioritize management actions is often opaque relative to why an index may have been originally developed. Numerous assessment products have been developed for specific regional applications (Birk et al. 2012) and concerns about redundancy, comparability, duplicated effort, and lack of coordinated monitoring have recently been discussed within the research community (Cao and Hawkins 2011, Poikane et al. 2014, Kelly et al. 2016, Nichols et al. 2016). Moreover, existing indices may not be easily replicated beyond initial research applications (Hering et al. 2010, Nichols et al. 2016) or may be incorrectly applied based on differences between goals for developing an index and the needs of management programs (Dale and Beyeler 2001, Stein et al. 2009). The abundance of available products can be a point of frustration for managers given a lack of guidance for choosing among alternatives, particularly as to how different assessment products relate to specific management, monitoring, or policy objectives (Dale and Beyeler 2001, Stein et al. 2009).

To address these challenges, a new mode of operation is needed where method development is open and transparent, developed products are discoverable and reproducible, and most importantly, implementation in the management community is intuitive and purposeful. Open science principles that democratize all aspects of the scientific method can help meet these needs and there is a unique opportunity in bioassessment to leverage openness to support public resources. Others have advocated more broadly for inclusion of open science principles in the ecological sciences (Hampton et al. 2015, 2016, Lowndes et al. 2017). Open science has also influenced how research workflows are conceptualized in other disciplines (e.g., archaeology, Marwick et al. 2016, behavioral ecology, Ihle et al. 2017, hydrology, Slater et al. 2019, vegetation sciences, Collins 2016). Adopting an open science paradigm in bioassessment is particularly relevant compared to other fields given the explicit need to develop products that are accessible to the management community. Legal and ethical precedents in bioassessment may also necessitate open data sharing given that environmental monitoring programs are often established to protect and maintain publicly-owned natural resources.

This review demonstrates tools and approaches for open science to empower the research and management community to embrace a new mode of thinking for bioassessment applications. These approaches are expected to benefit the bioassessment research community by augmenting existing workflows for developing assessment products and improving their ability to address environmental issues by bridging the gap between the scientific, management, and regulatory communities. As such, this paper is written primarily for the research team that develops bioassessment products, but we also write for the funders and users (e.g., regulators and managers) of these products to emphasize the value of investing in open science for the protection of public resources. Herein, open science "tools" describe best practices and specific applications that use an open philosophy to support applied science.

Principles of open science

Conventional modes of creating scientific products and more contemporary approaches that align with open science principles share the same goals. Both are motivated by guiding principles of the scientific method that make the process of discovery transparent and repeatable. Where the conventional and open science approaches diverge is the extent to which technological advances are leveraged as instrumental tools that facilitate the entire research process. Distinction between the two approaches can be conceptualized as the "research paper as the only and final product" for the conventional approach, whereas the open science approach is inherently linked to advances in communication and analysis that have been facilitated by the Internet and computer sciences (Table 1). As a result, the open science approach can enhance all aspects of the scientific process from initial conception of a research idea to the delivery and longevity of a research product (Fig. 1). The process is iterative where products are improved by the individual and/or others, facilitated by open science tools that enhance access and reproducibility of data.

The paradigm of the research paper as a final scientific product can inhibit the uptake of research methods and findings by environmental managers. The research paper is conventionally viewed as a communication tool for scientists to report and share results among peers. Researchers access periodicals to stay informed of scientific advances and use the information to replicate methods for follow-up analysis. Although the primary literature continues to provide these fundamental services, this workflow is problematic when scientific products are needed to serve interests outside of the research community. For example, the paper as an endpoint for environmental managers fails to deliver products that are easily accessible from the practitioners perspective, both in application and interpretation. A research paper is less likely to effect environmental change because it does not provide a mechanism to transfer actionable information to those that require scientific guidance for decision-making, such as sharing analysis code or results that describe output from assessment products. Numerous studies have documented implementation failures as a result of siloing among research communities where the flow of information does not extend beyond institutional walls (e.g., Mitchell 2005, Liu et al. 2008). Information loss over time is another well-known flaw associated with the paradigm of research paper as final product (Michener et al. 1997).

Open data as a component of the open science process

Open data is a fundamental component of the broader open science process in Fig. 1. Under this mode of thinking, the research team becomes stewards of its data. For bioassessment data, goverment institutions may be the primary stewards of information that supports product development within a broader research team. Stewardship allows the data to be treated as a living product with a traceable and replicable provenance (i.e., origin), rather than proprietary and serving only the internal needs of an immediate research goal. Metadata that describe the structure and history of a dataset ensure the data have an identity. Metadata also encourage adoption of core data structures that allow integration across different sources, which is critical for collaboration across institutional boundaries (Horsburgh et al. 2016, Hsu et al. 2017). Other open science practices, such as integration of data with dynamic reporting tools or submitting data to a federated repository (i.e., a decentralized database system for coordination and sharing), can facilitate communication for researchers and those for which the research was developed (Bond-Lamberty et al. 2016).

Open data can benefit research by contributing to an increase in novel products created through collaboration. Collaborative publications have increased in the environmental sciences as research teams leverage open data to create synthesis products that allow novel insights from comparisons across multiple datasets. Quantitative meta-analyses and systematic reviews are increasingly used to extract information from the primary literature (Lortie 2014). In addition, open data products can increase efficiency of the individual researcher and a collective research team by encouraging collaborators to adopt an open science workflow. Many tools developed within the software and computer science community to facilitate open process and the creation of open data are now easily accessible to environmental scientists. Version control software (e.g, Git, GitHub), open source programming languages (e.g, R, Python), and integrated development environments (IDEs, e.g., RStudio, Spyder) can all be leveraged to dynamically create and share open data products that build institutional memory. These tools promote deliberate and shared workflows among researchers that can lead to better science in less time (Lowndes et al. 2017) and have proven useful in recent applications in the hydrologic sciences (Idaszak et al. 2017, Slater et al. 2019).

Open access to data can also benefit management and regulatory communities. Openness can improve the value of data from monitoring programs by establishing workflows for data discovery and synthesis, often through the adoption of a common metadata structure and integration of data within federated data networks (e.g., DataONE, iRODS). Open data maintained by management or regulatory communities benefits the research community, which in turn benefits the data maintainers that require scientific products to inform decisions. Open data can also improve public trust in scientific findings by exposing the underlying information used to develop a research product (Grand et al. 2012). Similar concepts are used in "blockchain" technologies that allow public financial transactions in an open, distributed format, as for trading in cryptocurrencies (Pilkington 2016). Increased trust could facilitate eventual adoption of proposed rules or regulations that are based on research products created from open data. More efficient and effective implementation of potential rules may also be possible if supporting data are openly available.

Applying open science principles to bioassessment

Here we provide a detailed description of open science processes that the bioassessment community could leverage to create reproducible, transparent, and discoverable research products for environmental managers. The below examples require understanding the distinction between the general open science process in Fig. 1, open data as an individual component of the open science process, and the technology-based tools that can be used to achieve these ends. Both the tools and open data are critical components that facilitate the broader process to achieve the principles outlined in Table 1. However, open science tools can also be used by individual researchers in an entirely closed workflow with no collaboration or discoverability by others. Similarly, open data can be created through an entirely closed process even though it may appear as an open science product. "Openness" of process, tools, and data exists on a continuum, and incremental improvements can transform an individual's and research group's practice over time. We encourage awareness that an open process adopts the open science tools that are appropriate for a research question, the creation of open data can be a fundamental component of the process, and acceptance by the research team and collaborators of the concepts described in Table 1 is critical to achieving openness.

The overall process is shown in Fig. 2 as an expansion of general concepts in Fig. 1, with a specific science application phase for implementation. This iterative flow of information is facilitated by 1) openly sharing planning documents, 2) using established metadata standards to document synthesized data products, 3) hosting data products on open repositories, 4) creating reproducible summary documents that integrate the data and research products, and 5) incorporating the developed product into interactive applications that deliver the results to the managers and stakeholders. The technical phase of defining research goals, collecting and synthesizing data, and developing the bioassessment product are primary tasks of the research team. However, the process is distinguished by the flow of information to and from the research phase that can benefit the specific project and the science of bioassessment as a whole.

Developing bioassessment goals

In an open science process, the goals identified by the research team for developing a bioassessment product should occur through direct, two-way interaction with the management or regulatory institution that requires the product. This two-way exchange of information can be accomplished through direct communication and sharing of planning documents to ensure all decisions are transparent, i.e., open planning. In person meetings are ideal, but planning documents are dynamic and will require remote sharing and revision as ideas progress. Online tools such as Google documents, Slack discussion channels, and open lab notebooks can be instrumental for collaboration. More informal approaches, such as blogging and sharing ideas on social media, can expose new concepts to the broader community for guidance (Woelfle et al.

2011, Darling et al. 2013). Overall, the research team should use these tools to identify stakeholder needs while also considering the balance between the research goals and limitations of the data to meet these goals. This will ensure that the needs of the management and stakeholder communities will be consistent with the services provided by the research product.

Curating bioassessment data

After project goals are established, the research team identifies requirements and sources of data that need to be synthesized to meet the research needs. Bioassessment data, or more generally, biological data obtained from field sampling have a unique set of challenges that require added vigilance in data stewardship (Cao and Hawkins 2011). Taxonomic resolution requires a tradeoff between specificity with added cost (Lenat and Resh 2001, Chessman et al. 2007) and names change regularly requiring updates to standard taxonomic effort (STE) tables that are critical for many biological indices. Unidentified or ambiguous taxa must also be explicitly treated in analysis workflows (Cuffney et al. 2007), e.g., are they treated as missing values or are they substituted with coarser taxonomic designations? Environmental data that describe physical or chemical conditions are also critical to support development of an assessment index, as well as understanding potential stressors or background condition that could influence biological condition.

As an example, a multimetric index may require taxonomic data collected at multiple sites by different institutions, whereas the output data may include summary scores, individual metrics, and any additional supporting information to assess the quality of the output. These data products can easily be documented using a standardized metadata language (e.g., Ecological Metadata Language Standard, or EML) which describes the who, what, and why to ensure the data have an identity. Adoption of a metadata standard also ensures that a machine-readable file is produced to allow integration into a data repository. This will allow a synthesized data product to be discoverable beyond the specific research application and will provide metadata to help others understand the context of the data (e.g., Idaszak et al. 2017). Finally, the dataset can be assigned a unique digital object identifier (DOI, e.g., through Zenodo) that provides a permanent address and is also citable to allow researchers to track usage of a bioassessment data product.

In an open paradigm, the data itself is a product to achieve the research goals and also becomes available to the research and management community as a fully documented source of information that has value beyond the specific project. The openness of the synthesized data product is one of the primary means of facilitating the application of a bioassessment product. The synthesized data product can be used by the research team to create interactive applications for stakeholders to share and explore the data and is also fully integrated into summary reports using software for generating dynamic documents (e.g, using `knitr`, Xie 2015, RMarkdown, Allaire et al. 2018, Jupyter notebooks, Kluyver et al. 2016). The data product also becomes available on an open data repository that is discoverable by other researchers and can contribute to alternative scientific advances beyond the immediate goals (e.g., Hydroshare for the hydrologic sciences, Idaszak et al. 2017).

Using R for bioassessment application

The R statistical programming language (RDCT 2018) is one of the most commonly used analysis platforms in the environmental sciences (Lai et al. 2019, Slater et al. 2019) and many existing R packages have value for the bioassessment community (Table 2). For managing the day to day tasks of working with multiple datasets, the `tidyverse` suite of packages provides the necessary tools to import, wrangle, explore, and plot almost any data type (Wickham 2017). These packages are developed around the concept of "tidy" data that provide a common and natural framework for working with data (Wickham 2014). The `tidyverse` also includes the powerful `ggplot2` package that is based on a syntactical grammar of graphics for plotting (Wilkinson 2005, Wickham 2009). This package provides a set of independent plotting instructions that can be built piecewise and is a departure from other graphics packages that represent a collection of special cases that limit the freedom of the analyst. In bioassessment, `ggplot2` can be used both in an exploratory role during the development phase and also to create publication quality graphics. More importantly, this package provides the building blocks to create effective data visualizations that convey important components of a bioassessment product to managers and stakeholders.

Bioassessment data are inherently spatial and recent package development has greatly improved the ability to analyze and map geospatial data in R. The `raster` package can used to read/write, manipulate, analyze, and model grid-based spatial data (Hijmans 2019), which are often common supporting layers for bioassessment (e.g., elevation or climate data). For vector data (i.e., points, lines, and polygons), the `sf` package ("simple features", Pebesma 2018) was first released in 2016 and has quickly become the most highly-used approach for working with spatial information in R. The `sf` package uses principles of data storage that parallel those from the `tidyverse` by representing spatial objects in a tidy and tabular format. This facilitates analysis by presenting complex spatial structures in a readable format that can be integrated in workflows with existing packages, including other mapping packages (e.g., `leaflet`, Cheng et al. 2018, or `mapview`, Appelhans et al. 2018). This allows the research team to use a workflow that is focused in a single environment, rather than using separate software for statistical and geospatial analysis.

Several existing R packages can be used to develop statistical models of bioassessment data that are a necessary component of many analyses. Random forest models have been used to develop predictive bioassessment indices that compare observed taxa to modeled expectations (i.e., O/E indices). The `randomForest` package (Liaw and Wiener 2002) uses an ensemble learning approach that is robust to complex, non-linear relationships and interactions between variables. These models are particularly useful with large, regional datasets that describe natural and anthropogenic gradients in condition (Laan and Hawkins 2014, Mazor et al. 2016). Many other modeling packages are available in R that can support index development, such as exploratory analyses to evaluate biological response or identifying significant associations of organisms with stressor gradients. The `nlme` package can be used to create non-linear mixed effect models that are more flexible than standard regression approaches (Pinheiro et al. 2018). The `nlme` package can develop models for nested sampling designs, such as repeat visits to sample sites or otherwise confounding variables that contribute information but are not unique observations (Mazor et al. 2014). The `mgcv` package provides similar functionality as `nlme`, but uses an additive modeling approach where individual effects can be evaluated as the sum of smoothed terms (Wood 2017). The `mgcv` package is often applied to model biological response to stressor gradients (Yuan 2004, Taylor et al. 2014)

Other R packages have been developed specifically for bioassessment. For example, the `TITAN2` package can be used to develop quantitative evidence of taxon-specific changes in abundance and occurrence across environmental gradients (Baker et al. 2015). Results from this package can support exploratory analysis for developing bioassessment products, such as identifying indicator species or establishing numeric criteria (Taylor et al. 2018). The results can be also be used post hoc to evaluate potential response of a biological index with changing environmental conditions, such as proposed management actions for rehabilitation (King et al. 2011). Alternatively, the `indicspecies` package provides similar functionality but is based only on species occurrence or abundance matrices across sites (De Caceres and Legendre 2009). This package can be used to identify species that occur at particular sites if continuous environmental data are unavailable, such as those that are representative of reference conditions (Bried et al. 2014). Finally, the `vegan` package has been a staple among community ecologists for multivariate analyses in R, such as clustering and ordination (Oksanen et al. 2018).

Although the R network includes over 10000 user contributed packages, only a handful of these packages are specific to bioassessment. Community practices have allowed R to reach new audiences where new packages build on the work of others and are transportable between users and operating systems, rather than all researchers reinventing the wheel through duplicated effort. Formalized communities, such as rOpenSci, encourage standardization and review of contributed packages within the ecological sciences to make scientific data retrieval reproducible. Several tools have also been developed and published in the last five years that greatly simplify the process of creating new packages in R (Wickham 2015, Wickham et al. 2018). The advantages of creating and sharing R packages that are specific to bioassessment applications are important for several reasons. First, an R package compartmentalizes technical instructions developed during the research phase that can be executed by anyone with access to the software. This allows the technical elements required for the execution of a bioassessment product to be included, while allowing the end user to focus on how the output can be used to inform decision-making. R packages also require explicit documentation of the functions and data requirements. As such, package users will not only have access to underlying code but also understand the why and what for different package functions.

Finally, R can be used to create interactive applications that deliver bioassessment products to stakeholders and managers in entirely novel contexts. In particular, the `shiny` package was first released for R in 2012 and provides programming tools built around concepts of reactivity, where data inputs and outputs can be modified in real time (Chang et al. 2018). A `shiny` application is an interactive user interface that is developed with R code, but is a standalone product that can be used without any programming experience. These applications are deployed online and can extend the reach of bioassessment products to those that require the information for decision-making but otherwise do not have the time or resources to learn R. Applications built in `shiny` can also be easily linked to other R packages. For example, a `shiny` website could be created to allow users to upload raw data and estimate and report bioassessment scores using an R package developed externally. This can extend the accessibility of a bioassessment product while maintaining the technical integrity of the original tool. Moreover, `shiny` applications are completely customizable and can be tailored by the developer to the specific needs of any user. This distinction separates `shiny` from other web-based analysis platforms.

Open science in practice: The SCAPE project

Although bioassessment products have been sufficiently developed in California (USA), there are no narrative or numeric criteria in place to support designated aquatic life uses in wadeable streams, nor are bioassessment data actively used to support conservation or watershed management. Indices using benthic macroinvertebrates and algae have been developed that provide consistent indications of biological condition across the diverse geography and climates in the state (Fetscher et al. 2013, Mazor et al. 2016, Ode et al. 2016). A physical habitat index has also been developed that provides complementary information supporting bioassessment data (Rehn et al. 2018). Combined, these indices represent significant achievements in overcoming technical challenges for developing accurate and interpretable bioassessment products. However, these products are not used at a statewide scale to inform decisions and past efforts for stream management have only used a fraction of available products. A synthesis of condition assessments is needed to effectively implement bioassessment products in California and data must be presented in a context that is relevant to the needs of decision makers.

Recent regulatory initiatives in California have established a foundation for openness that could greatly improve the application of bioassessment products to support decision-making. In particular, these initiatives have set a precedent for openly sharing data collected with public funds. The Open and Transparent Water Data Act passed by the state legislature in 2016 requires water quality institutions to "create, operate, and maintain a statewide integrated water data platform that, among other things, would integrate existing water and ecological data information from multiple databases and provide data on completed water transfers and exchanges" (AB 1755, Dodd, 2015-2016). This legislation also calls for state agencies to "develop protocols for data sharing, documentation, quality control, public access, and promotion of open-source platforms and decision support tools related to water data". These aspirations were further supported by a resolution on July 10, 2018 that formally committed the State Water Resources Control Board to "provide broader access to data used to make local, regional, and statewide water management and regulatory decisions in California". These recent initiatives in California have similarly been observed at the national level. For example, the Data Coalition is an advocacy group that operates on behalf of the private and public sector for the publication of government data in a standardized and open format. The Internet of Water also operates at the national-level by focusing on strengthening connections between data producers and users through centralized data hubs and data standards.

Open science tools have recently been used in California to address bioassessment implementation challenges in developed landscapes. The Stream Classification and Priority Explorer, or SCAPE (Beck 2018a, Beck et al. in press), was developed using an open science framework to help identify reasonable management goals for wadeable streams using existing bioassessment and watershed data. The SCAPE tool represents both a modeling approach to help prioritize management goals (Fig. 3) and a set of open science products for direct application to environmental managers. The modeling component addresses a practical problem of achieving reference conditions in developed landscapes, where channel modification is common. Using the National Hydrography Dataset (NHD-Plus; McKay et al. 2012) and watershed predictors (StreamCat; Hill et al. 2016), the model classifies stream segments as biologically "constrained" or "unconstrained" by landscape alteration. This classification system can be used to set management priorities based on the constraint class. For example, a monitoring site with an observed biological index score that is above a predicted range could be assigned a higher management priority relative to a site that is scoring within the range that is expected based on landscape development.

Open science tools were critically important for translating and delivering SCAPE products to decision-makers. Local stakeholder engagement to identify research goals guided the technical development process of SCAPE. All analyses, including model development and validation, were conducted using R. A version control system (Git) and online hosting (GitHub) also allowed full transparency of decisions that were made to create the SCAPE model. A permanent

DOI was assigned through Zenodo to track downloads and portability of source code (Beck 2018a). Importantly, an online, interactive web page (https://sccwrp.shinyapps.io/SCAPE) greatly increased the impact and relevance of SCAPE by improving stakeholder understanding through direct interaction with key decision points that influenced model output. A manuscript describing the technical components of the model was created using `knitr` and `RMarkdown` (Xie 2015, Allaire et al. 2018). This increased efficiency of the writing process also minimized the potential of introducing errors into tables or figures by eliminating the need to copy results between different writing platforms. Finally, a geospatial data file from the model was also made public on a federated data repository, which included metadata and plain language documentation to track provenance of the original information (Beck 2018b).

Limitations and opportunities

Although the case for open science in bioassessment is appealing, the widespread adoption of these principles in practice is inhibited by inertia of existing practices, disciplinary culture, and institutional barriers. Conventional and closed workflows used by many scientists are adopted and entrenched because of ease of use, precedence, and familiarity, yet they can be inefficient, inflexible, and difficult to communicate or replicate. Open science tools can improve analysis, documentation, and implementation through greater flexibility, but they expose research teams to entirely new concepts and skillsets in which they may never have been trained (e.g., Idaszak et al. 2017). Not only are the required skillsets demanding, but the open science toolbox continues to expand as new methods are developed and old methods become obsolete. This requires a research team to stay abreast of new technologies as they are developed and weigh the tradeoffs of adopting different workflows for different research tasks.

Advocates for open science are well aware of the technical challenges faced by individuals and research teams that have never been exposed to the core concepts. Most importantly, education and training (e.g., through The Carpentries) remain key components for developing skillsets among researchers where the focus is both on learning new skills for transferability and realizing their value for improving science as a whole (Hampton et al. 2017). A goal of many training curricula is to instill confidence in new users by developing comfort with new workflows, such as replacing a point-and-click style of analysis with one focused on using a command line through a computer terminal. Other approaches to demonstrate the value of new techniques use a side by side approach of closed vs open workflows to show the increased efficiency and power of the latter. Adoption becomes much more reasonable once users realize the value of investing in learning a new skill.

Advocates of open science also recognize the limitations of teaching in that not all audiences can be reached and not all materials are retained or even used after training. A strategy of empowering trainees to become trainers and teach others at their home institutions (e.g., train-the-trainer workshops and programs) enables open science to reach more individuals, and benefits science more broadly as they develop technical and communication skills, and build local communities. Those that also adopt new workflows through training can also direct their research products to facilitate collaboration with non-adopters rather than the latter synthesizing and analyzing their data in potentially suboptimal ways (Touchon and McCoy 2016). These "champions" can be a voice of encouragement for others by demonstrating how new tools can be introduced and learned over time through shared experiences (Lowndes et al. 2017). This also encourages the development of a community of practice that shares and learns together to navigate the collection of existing and developing open science tools. Champions of open science should also be vocal proponents that spread awareness of the value of open science tools, particularly to those that make decisions on project resources. Department heads or administrative leaders may not be aware of the value of investing in open science, particularly if the consequences of not doing so are externalized in indirect costs that are not budgeted. A change in mindset may be needed where open science is viewed as a core tool that is critical to maintaining relevance of a research program in the future (Hampton et al. 2017).

Many scientists feel they cannot prioritize learning new skills given existing demands on their time, particularly if the benefits of these approaches, such as the value for the research team of sharing their data, are not apparent or immediate. Short-term funding and even political cycles can disincentivize scientists from spending time on anything but contractually obligated deliverables, which as noted above, may not effectively apply science in decision-making. This is an acute concern for early career scientists that have higher demands on establishing reputation and credentials, where investments in open science may be seen as detracting from progress (Allen and Mehler 2019). As an alternative, a practical solution is to actively encourage the investment in open science within the research team or lab, as opposed to placing the burden on the individual as an isolated researcher (i.e., team science, Cheruvelil and Soranno 2018). Laboratory or department heads should allow and encourage research staff to invest time in learning new skills and exploring new ideas, even if this does not immediately benefit the latest project. Over time, small investments in developing new skills will have long-term payoffs, particularly if a growing skillset among the research team encourages networking and peer instruction (Lowndes et al. 2017, Allen and Mehler 2019). Developing an environment where open science tools are highly valued and encouraged may also increase job satisfaction and benefit recruitment and retention if researchers are allowed the space and time to develop skills beyond the current project.

The scientific culture within a discipline or institution may inhibit the adoption of open science methods. A common argument against open science is the protection of data that an individual research team may view as proprietary or sensitive. There are reasonable arguments to treat data as personal property, particularly if exceptional effort was spent to secure funding for a project and if the data were hard-earned or sensitive, e.g., detailed location data on endangered species or medical/socioeconomic data (Zipper et al. 2019). These issues are less of a concern for bioassessment where many datasets are collected by institutions that are publicly funded and data accessibility may be mandated by law. However, an open science process dictates that both interim and completed research products derived from public data should be available to the broader bioassessment community. This raises an additional concern that research teams using transparent workflows could expose themselves to increased criticism by their peers and the public (Lewandowsky and Bishop 2016, Allen and Mehler 2019), particularly where the developed products can have important regulatory implications.

Feedback and criticism are fundamental and natural parts of the scientific process. Scientists receive feedback at many stages in the conventional scientific workflow (e.g., internal review, peer-review, presentations at conferences). Potentially new and challenging avenues for feedback are created in an open workflow. A concern is that openness can provide a platform for antagonistic or even hostile views, which could alter or degrade the scientific product (Landman and Glantz 2009, Lewandowsky and Bishop 2016). However, opportunities for addressing alternative viewpoints are critical to the open process of creating applied products, even if some voices are politically charged. This is especially true in bioassessment where finished products that could be adopted in regulation are often heavily scrutinized. It is in the interest of applied scientists to hear the concerns of all parties during the development phase. This is not to provide an avenue to erode the integrity or objectives of the science, but to enable full knowledge of the very real barriers to adoption that exist when science is applied in regulation. Openness that invites all voices to participate is a much more agreeable path to consensus than producing the science in isolation of those that it affects (Pohjola and Tuomisto 2011). Ultimately, these products are developed to improve the environment as a public resource and the ideals promoted by an open science process directly align with these goals.

Institutional barriers can inhibit open science given the scale of change that must occur for adoption. Bureaucratic hurdles can disincentivize initiatives that promote change, particularly if that change originates from researchers not in administrative roles. Regulatory institutions may also prefer some level of opacity for how research products that influence policy are made available during development. The level of transparency advocated by open science could be viewed as opening the floodgates to increased legal scrutiny that can unintentionally hinder forward progress. Despite these reservations, many public institutions now advocate for increased openness because of the benefits that facilitate and engender public trust. Open data initiatives are now fairly common and represent a form of advocacy by public institutions for broader adoption of open science principles. Many national-level data products already exist that embrace openness to invest in the quality and availability of data (e.g., National Wata Quality Monitoring Council initiatives, US Geological Survey products through NWIS and BioData, US Environmental Protection Agency through STORET/WQX). Although past efforts and recent changes represent progress, many institutions have yet to strictly define open science and how it is applied internally and externally. As open science continues to build recognition, means of integrating toolsets that promote openness and transparency beyond publicly shared data will have to be adopted by regulatory and management institutions.

Conclusions

The relevance of bioassessment applications can be improved with open science by using reproducible, transparent, and effective tools that bridge the gap between research and management. Many open science tools can improve communication between researchers and managers to expose all aspects of the research process and facilitate implementation to support policy, regulation, or monitoring efforts. Communication ensures that the developed product is created through an exchange of ideas to balance the potentially competing needs of different sectors and institutions. The documentation and archiving of data used to create a bioassessment product also ensures that other researchers can discover and build on past efforts, rather than constantly rebuilding the wheel. Incremental improvements of existing products can reduce the proliferation of site- and taxon-specific methods with limited regional applications by exploring new ways to integrate biological indicators across space and time.

Author contributions

MB and RM performed the research in the case study. All authors contributed to the conceptual development and writing of the manuscript.

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Figures

Fig. 1: A simplified workflow of the open science paradigm (adapted from Hampton et al. 2015). All aspects of the research process, from the conception of an idea to publishing a product, can be enhanced using open science tools. The workflow is iterative where products are continually improved through collaborations facilitated through discovery and reproducibility of open data.

Fig. 2: An idealized open approach for bioassessment applications. The green box represents the technical steps of the individual research team for developing the product, the manager and stakeholder box are those that require or motivate the creation of bioassessment products, the gray boxes indicate sources of external information (data and guidance documents) as input into the technical process, and the open text indicates open components of the planning, application, or implementation phase of a bioassessment product. Figures were adapted from Hampton et al. (2015). NGO: non-government organization, RMP: regional monitoring program.

Fig. 3: Schematic demonstrating how the Stream Classification and Community Explorer (SCAPE) can be used to identify potential management actions for stream sites. Stream segment classifications are defined as biologically constrained or unconstrained based on landscape characteristics (left map) and sites with bioassessment scores are evaluated relative to the classifications. Sites can be under-scoring, as expected, or over-scoring relative to the segment classification and expected range of scores (middle plot). Unconstrained sites are those where present landscape conditions do not limit biological potential and constrained sites are those where landscape conditions limit biological potential (right images). Management actions and priorities can be defined based on site scores relative to segment classifications.

Tables

Table 1: Core definitions and principles of open science, from Open Knowledge International, http://opendefinition.org/, Creative Commons, https://creativecommons.org/about/program-areas/open-science/, and D. Gezelter, http://openscience.org/

Concepts.and.principles	Description
Open	Anyone can freely access, use, modify, and share for any purpose
Open Science	The practice of science in such a way that others can collaborate and contribute, where research data, lab notes and other research processes are freely available, under terms that enable reuse, redistribution and reproduction of the research and its underlying data and methods
Principle 1	Transparency in experimental methodology, observation, and collection of data
Principle 2	Public availability and reusability of scientific data
Principle 3	Public accessibility and transparency of scientific communication
Principle 4	Using web-based tools to facilitate scientific collaboration and reproducibility

Table 2: R packages that can be used in the development and application of bioassessment products.

Task	Package	Description
General	`tidyverse` (Wickham 2017)	A suite of packages to import, wrangle, explore, and plot data. Includes the popular `ggplot2` and `dplyr` packages.
Mapping, geospatial	`sf` (Pebesma 2018)	A simple features architecture for working with vectorized spatial data, including common geospatial analysis functions
	`raster` (Hijmans 2019)	Reading, writing, manipulating, analyzing, and modeling gridded spatial data
	`leaflet` (Cheng et al. 2018)	Integration of R with the popular JavaScript `leaflet` library for interactive maps
	`mapview` (Appelhans et al. 2018)	Creates interactive maps to quickly examine and visually investigate spatial data, built off `leaflet` and integrated with `sf`
Statistical modeling	`randomForest` (Liaw and Wiener 2002)	Create classification and regression trees for predictive modeling
	`nlme` (Pinheiro et al. 2018)	Non-linear, mixed effects modeling
	`mgcv` (Wood 2017)	Generalized additive modeling
Community analysis	`TITAN2` (Baker et al. 2015)	Ecological community threshold analysis using indicator species scores
	`indicspecies` (De Caceres and Legendre 2009)	Indicator species analysis
	`vegan` (Oksanen et al. 2018)	Multivariate analysis for community ecology
Science communication	`shiny` (Chang et al. 2018)	Reactive programming tools to create interactive and customizable web applications
	`rmarkdown` (Allaire et al. 2018)	Tools for working with markdown markup languages in .Rmd files
	`knitr` (Xie 2015)	Automated tools for markdown files that process integrated R code chunks

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Fig1

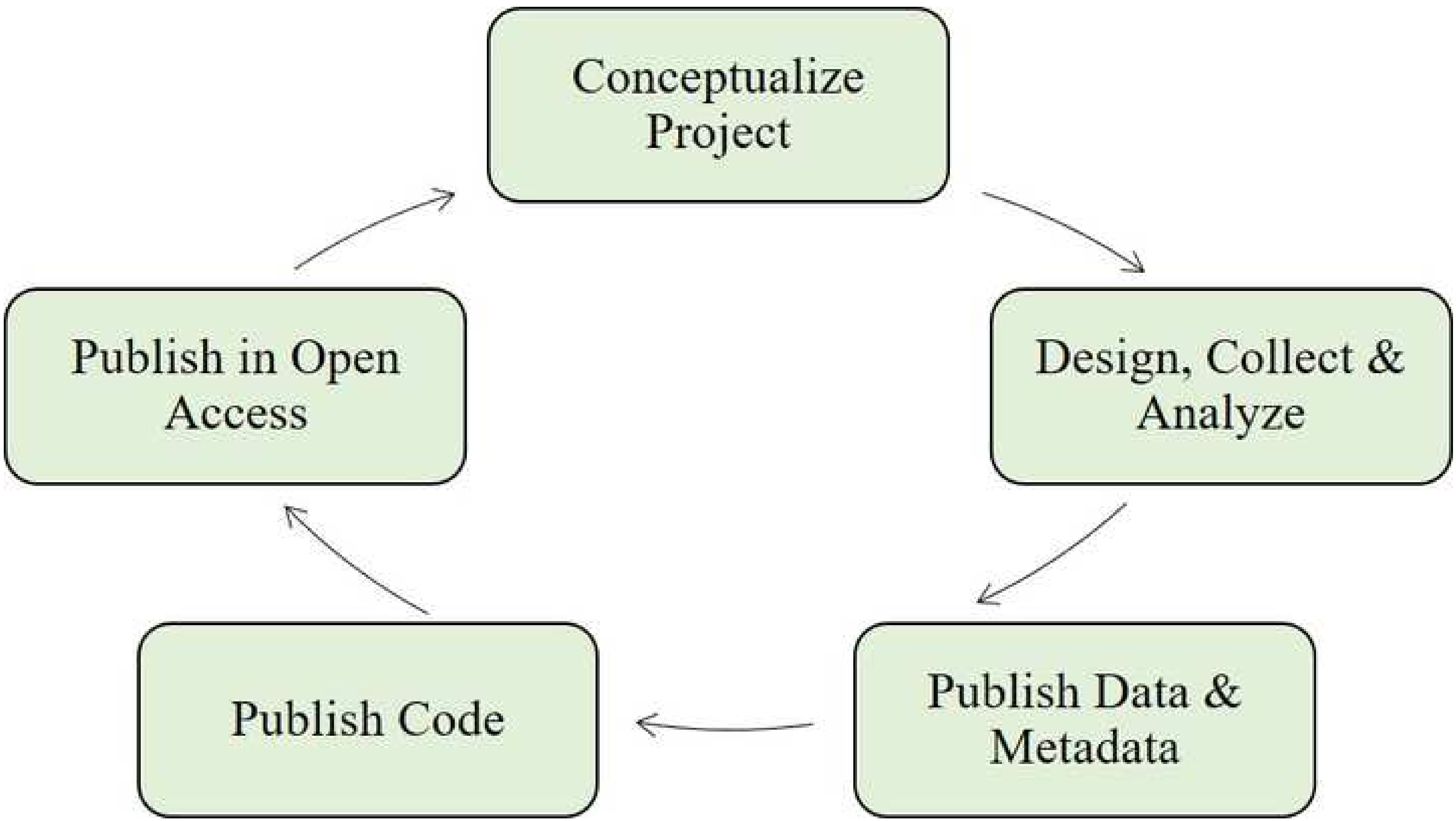

Conceptualize Project
Design, Collect & Analyze
Publish Data & Metadata
Publish Code
Publish in Open Access

Fig2

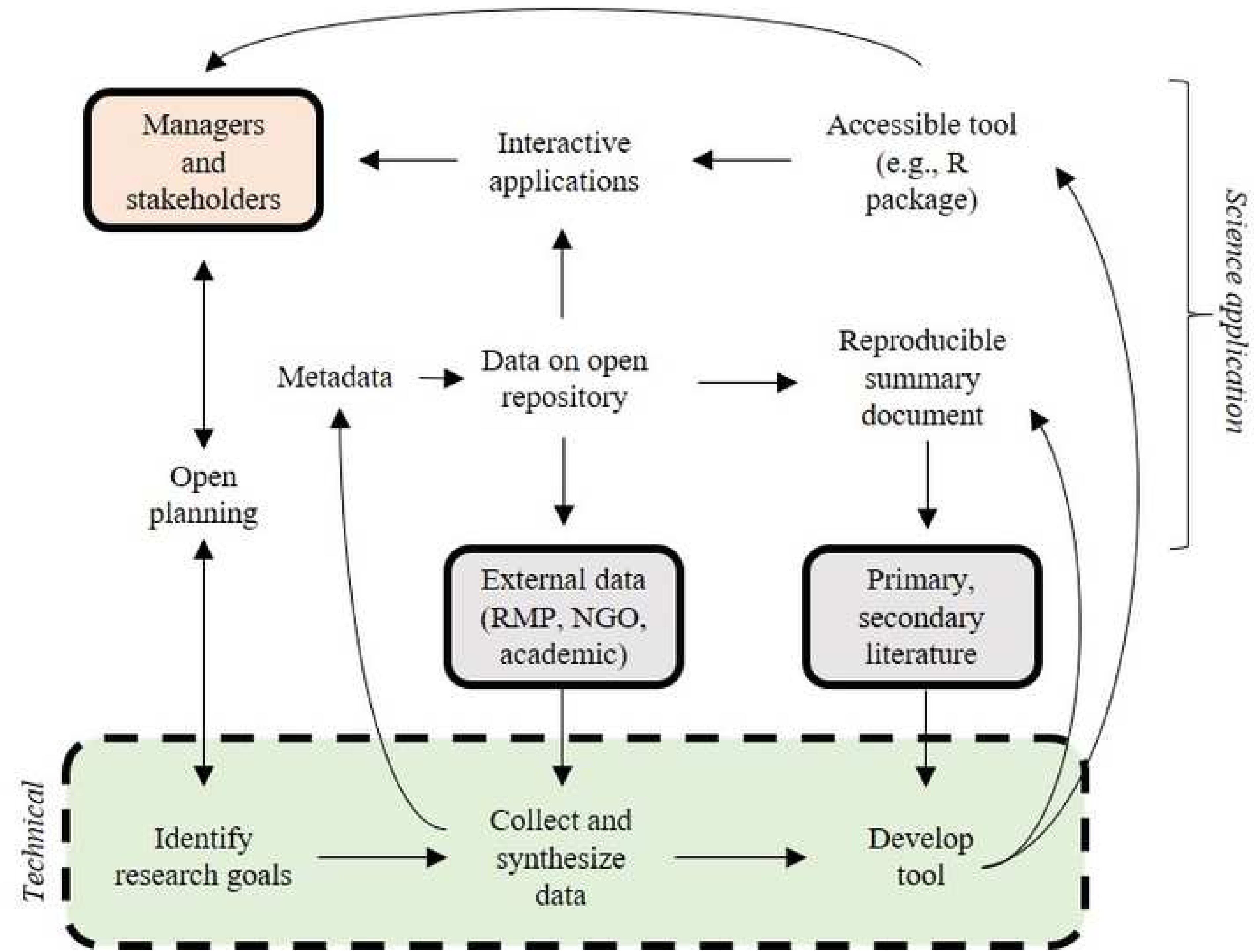
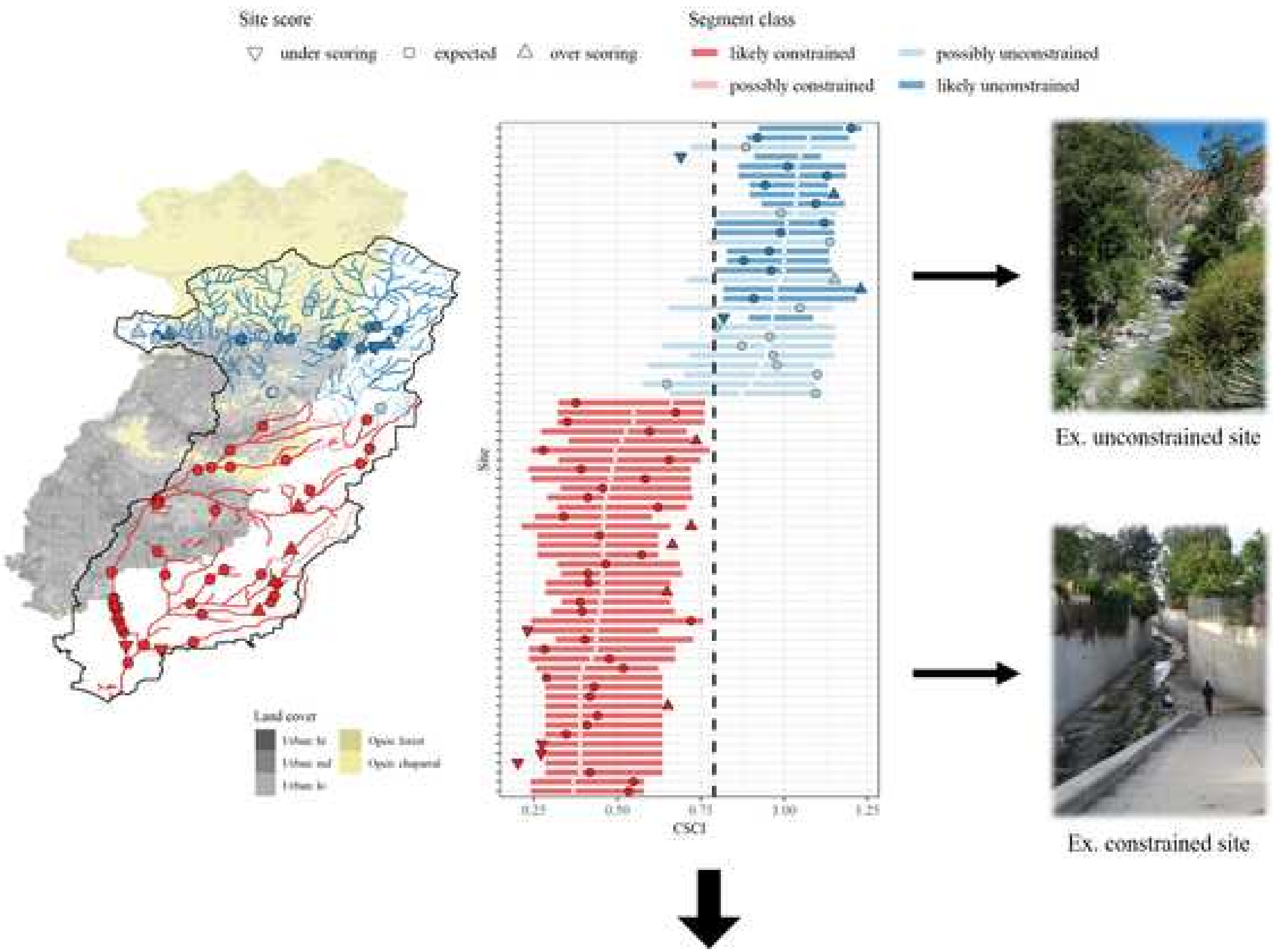

Managers and stakeholders
Interactive applications
Accessible tool (e.g., R package)
Science application
Metadata
Data on open repository
Reproducible summary document
Open planning
External data (RMP, NGO, academic)
Primary, secondary literature
Technical
Identify research goals
Collect and synthesize data
Develop tool

Fig3



Action	Example activity	Example high priority site	Example low priority site
Investigate	Higher frequency of sampling, evaluate additional data (e.g., habitat)	Sites scoring outside prediction interval	Sites scoring as expected
Protect	Extra scrutiny of proposed impacts	Unconstrained sites	Constrained sites
Restore	Make funding recommendations, prioritize TMDL development	Low-scoring unconstrained sites	Low-scoring constrained sites