The importance of open science for biological assessment of aquatic environments

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Open science principles that seek to improve 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.

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21 Abstract

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24 for the development and application of bioassessment products. At the core of this philosophy is
25 the concept that research should be reproducible and transparent, in addition to having long-term
26 value through effective data preservation and sharing. In this paper, we review core open science
27 concepts that have recently been adopted in the ecological sciences and emphasize how adoption
28 can benefit the field of bioassessment for both prescriptive condition assessments and proactive
29 applications that inform environmental management. An example from the state of California
30 demonstrates effective adoption of open science principles through data stewardship,
31 reproducible research, and engagement of stakeholders with multimedia applications. We also
32 discuss technical, sociocultural, and institutional challenges for adopting open science, including
33 practical approaches for overcoming these hurdles in bioassessment applications.

Introduction

34

35 Bioassessment is an essential element of aquatic monitoring programs that helps guide decisions
36 for managing the ecological integrity of environmental resources. Legal mandates to assess
37 biological condition have stimulated the development of bioassessment programs and tools in the
38 United States (Clean Water Act, CWA), Canada (Canada Waters Act), Europe (Water
39 Framework Directive), China (Environmental Quality Standards for Surface Water), South
40 Africa (National Water Act), and elsewhere (Borja et al. 2008). Decades of research have
41 supported the development of assessment indices for multiple assemblages with regional
42 applications in streams, rivers, lakes, and marine environments (Karr et al. 1986, Kerans and
43 Karr 1994, Fore and Grafe 2002, Beck and Hatch 2009, Borja et al. 2009, 2016). Substantial
44 technical advances have been made in measuring biological responses to environmental change
45 (Hawkins et al. 2000a, 2000b), how these responses can be distinguished from natural
46 environmental variation (Stoddard et al. 2006, Hawkins et al. 2010), and interpreting the impacts
47 of these changes (Davies and Jackson 2006).

48 Integrating bioassessment products (e.g., scoring indices, causal assessment protocols) into
49 management or regulatory frameworks can be challenging, despite the technological advances
50 (Kuehne et al. 2017). How a bioassessment product is used in practice to inform decisions and
51 prioritize management actions can differ from why it may have been originally developed.
52 Numerous assessment products have been developed for specific regional applications (Birk et
53 al. 2012) and concerns about redundancy, comparability, duplicated effort, and lack of
54 coordinated monitoring have recently been highlighted (Cao and Hawkins 2011, Poikane et al.
55 2014, Kelly et al. 2016, Nichols et al. 2016). Kuehne et al. (2019) recently highlighted a lack of
56 institutional connectivity among actors with expertise in freshwater assessment as a hallmark of
57 the status quo in which applied science is conducted. Moreover, existing indices may not be
58 easily calculated by others beyond initial research applications (Hering et al. 2010, Nichols et al.
59 2016) or may be incorrectly applied based on differences between goals for developing an index
60 and the needs of management programs (Dale and Beyeler 2001, Stein et al. 2009). The
61 abundance of available products can be a point of frustration for managers given a lack of
62 guidance for choosing among alternatives, particularly as to how different assessment products
63 relate to specific management, monitoring, or policy objectives (Dale and Beyeler 2001, Stein et
64 al. 2009).

65 To address these challenges, a new mode of operation is needed where method development is
66 open and transparent, developed products are discoverable and reproducible, and most
67 importantly, implementation in the management community is intuitive and purposeful. Open
68 science principles that improve all aspects of the scientific method can help meet these needs and
69 there is a unique opportunity in bioassessment to leverage openness to support public resources.
70 Open science and its ideals originated partly due to failures of reproducibility and biases in the
71 primary literature that were revealed as systematic concerns in research fields with immediate
72 implications for human health (Makel et al. 2012, Franco et al. 2014). These ideas and the
73 failures that they address have slowly permeated the ecological and environmental sciences
74 (Hampton et al. 2015, 2016, Lowndes et al. 2017). Open science has also influenced how
75 research workflows are conceptualized in other disciplines (e.g., archaeology, Marwick et al.
76 2016, behavioral ecology, Ihle et al. 2017, hydrology, Slater et al. 2019, vegetation sciences,
77 Collins 2016) and has enabled a shift towards publishing structures that are more fair and

78   transparent through open access (Oudenhoven et al. 2016, Essl et al. 2020). Limited examples
79   have suggested that open access databases can be leveraged to develop bioassessment products
80   that increase transparency among stakeholders (Borja et al. 2019). Adopting an open science
81   paradigm in bioassessment is particularly relevant compared with other fields given the explicit
82   need to develop products that are accessible to the management community. Legal and ethical
83   precedents in bioassessment may also necessitate open data sharing given that environmental
84   monitoring programs are often established to protect and maintain publicly-owned natural
85   resources.

Survey Methodology and Objectives

87   This review draws on previous literature to describe approaches for open science that can
88   empower the research and management community to embrace a new mode of thinking for
89   bioassessment applications. These approaches are expected to benefit the bioassessment research
90   community by providing new tools that augment existing workflows for developing assessment
91   products and improving their ability to address environmental issues by bridging the gap
92   between the scientific, management, and regulatory communities. The intended audience for this
93   review is primarily the research team that develops bioassessment products, but we also write for
94   the funders and users (e.g., regulators and managers) of these products to emphasize the value of
95   investing in open science for the protection of public resources.

96   This traditional review covers literature published in recent years advocating for open science in
97   different fields of study. Because no similar efforts have yet been made to apply these principles
98   to bioassessment, we draw on examples from the previous literature that demonstrate successful
99   applications in other fields to motivate researchers and practitioners to embrace these new ideas
100   in bioassessment. Comprehensive and unbiased coverage of the previous literature was
101   accomplished by querying online search engines, primarily Google Scholar, with search terms as
102   they relate to open science (e.g., "reproducibility", "data science", "open source") and with
103   Boolean operators to find applications to bioassessment (e.g., "reproducibility AND
104   bioassessment"). Studies were included if they provided general overview of open science
105   concepts that were relevant to bioassessment or if they directly described open science
106   applications to bioassessment, although the latter were scarce. Emphasis was given to the breadth
107   of research that has supported the development of open source software applications that can aid
108   bioassessment, both as general tools and more specific programs tailored for indicator
109   development. We excluded studies that described applications with citizen science components.
110   Although citizen science can be a valuable tool for researchers and managers, methods for
111   effective implementation are beyond the scope of this review.

112   Our objectives are to 1) provide a general overview of principles of open science and 2)
113   empower the research community by providing examples of how these principles can be applied
114   to bioassessment. For the second objective, we also provide a case study of stream bioassessment
115   in the urban landscape of southern California to demonstrate a successful proof of concept.
116   Herein, open science 'tools' describe best practices and specific applications that use an open
117   philosophy to support applied science. We structure the review by first introducing open science
118   principles, then describing how these principles could be applied to bioassessment (i.e.,
119   developing goals, curating data, and applying open-source software) including a case study

120   example, and lastly providing a discussion of limitations and opportunities to better contextualize
121   real world applications of open science.

Principles of open science

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

135   The paradigm of the research paper as a final scientific product can inhibit the uptake of research
136   methods and findings by environmental managers. The research paper is conventionally viewed
137   as a communication tool for scientists to report and share results among peers. Researchers
138   access periodicals to stay informed of scientific advances and use the information to replicate
139   and improve on methods for follow-up analysis. Although the primary literature continues to
140   serve this critical role, this workflow is problematic when scientific products are needed to serve
141   interests outside of the research community. For example, the paper as an endpoint for
142   environmental managers fails to deliver products that are easily accessible from the practitioner's
143   perspective, both in application and interpretation. A research paper is less likely to effect
144   environmental change because it does not provide a mechanism to transfer actionable
145   information to those that require scientific guidance for decision-making, such as sharing
146   analysis code or results that describe output from assessment products. Numerous studies have
147   documented implementation failures as a result of siloing among research communities where
148   the flow of information does not extend beyond institutional walls (e.g., Mitchell 2005, Liu et al.
149   2008). Information loss over time is another concern associated with the paradigm of research
150   paper as final product (Michener et al. 1997), particularly as intimate knowledge of study details
151   is lost as new projects are initiated or individuals leave institutions.

Open data as a component of the open science process

153   Open data is a fundamental component of the broader open science process described in Figure
154   1. Under this mode of thinking, the research team becomes stewards of its data. For
155   bioassessment data, government institutions may be the primary stewards of information that
156   supports product development within a broader research team. Stewardship allows the data to be
157   treated as a dynamic product with a traceable and replicable provenance (i.e., origin), rather than
158   proprietary and serving only the internal needs of an immediate research goal. Metadata that
159   describe the structure and history of a dataset ensure the data have an identity. Metadata also
160   encourage adoption of core data structures that allow integration across different sources, which
161   is critical for collaboration across institutional boundaries (Horsburgh et al. 2016, Hsu et al.

162 2017). Other open science practices, such as integration of data with dynamic reporting tools or
163 submitting data to a federated repository (i.e., a decentralized database system for coordination
164 and sharing), can facilitate communication for researchers and those for which the research was
165 developed (Bond-Lamberty et al. 2016). Prominent examples that can benefit next-generation
166 bioassessment methods, such as molecular-based techniques for species identification, include
167 the BarCode of Life Data Systems (BOLD) and GenBank repositories.

168 Open data can benefit research by contributing to an increase in novel products created through
169 collaboration. Collaborative publications have increased in the environmental sciences as
170 research teams leverage open data to create synthesis products that allow novel insights from
171 comparisons across multiple datasets. Quantitative meta-analyses and systematic reviews are
172 increasingly used to extract information from the primary literature (Carpenter et al. 2009, Lortie
173 2014). In addition, open data products can increase efficiency of the individual researcher and a
174 collective research team by encouraging collaborators to adopt an open science workflow. Many
175 tools developed within the software and computer science community to facilitate open process
176 and the creation of open data are now easily accessible to environmental scientists (Yenni et al.
177 2019). Version control software (e.g., Git, GitHub), open source programming languages (e.g.,
178 R, Python), and integrated development environments (IDEs, e.g., RStudio, Spyder) can all be
179 leveraged to dynamically create and share open data products that can build institutional
180 memory. These tools promote deliberate and shared workflows among researchers that can lead
181 to better science in less time (Lowndes et al. 2017) and have proven useful in recent applications
182 in the hydrologic sciences (Idaszak et al. 2017, Slater et al. 2019).

183 Open access to data can also benefit management and regulatory communities. Openness can
184 improve the value of data from monitoring programs by facilitating data discovery and synthesis,
185 often through the adoption of a common metadata structure and integration of data within
186 federated data networks (e.g., DataONE, iRODS). Research institutions can also use open data
187 maintained by management or regulatory communities to develop products that directly support
188 the mission of the latter, e.g., assessment methods developed from long-term monitoring datasets
189 that identify priority areas to focus management actions or fulfill regulatory obligations. Open
190 data can also improve public trust in scientific findings by exposing the underlying information
191 used to develop a research product (Grand et al. 2012). Similar concepts are used in
192 "blockchain" technologies that allow public financial transactions in an open, distributed format,
193 as for trading in cryptocurrencies (Pilkington 2016). Increased trust could facilitate eventual
194 adoption of proposed rules or regulations that are based on research products created from open
195 data. More efficient and effective implementation of potential regulations may also be possible if
196 supporting data are openly available.

Applying open science principles to bioassessment

198 Here we provide a detailed description of open science processes that the bioassessment
199 community could leverage to create reproducible, transparent, and discoverable research
200 products for environmental managers. The below examples require understanding the distinction
201 between the general open science process in Figure 1, open data as an individual component of
202 the open science process, and the technology-based tools that can be used to achieve these ends.
203 Both the tools and open data are critical components that facilitate the broader process to achieve
204 the principles outlined in Table 1. "Openness" of process, tools, and data exists on a continuum,

205 and incremental improvements can transform an individual's and research group's practice over
206 time. We encourage awareness that an open process adopts the open science tools that are
207 appropriate for a research question and the creation of open data can be a fundamental
208 component of the process. Acceptance by the research team and collaborators of the concepts
209 described in Table 1 is critical to achieving openness.

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

Developing bioassessment goals

221 In an open science process, the goals identified by the research team for developing a
222 bioassessment product should occur through direct, two-way interaction with the management or
223 regulatory institution that requires the product. Although such an approach has historically been
224 used to develop bioassessment products, the interaction in an open science workflow differs in
225 how information is exchanged. This exchange can be accomplished through direct
226 communication and sharing of planning documents to ensure all decisions are transparent, i.e.,
227 open planning. In person meetings are ideal, but planning documents are dynamic and will
228 require remote sharing and revision as ideas progress. Online tools such as Google documents,
229 Slack discussion channels, and open lab notebooks can be instrumental for collaboration. More
230 informal approaches, such as blogging and sharing ideas on social media, can expose new
231 concepts to the broader community for guidance (Woelfle et al. 2011, Darling et al. 2013).
232 Overall, the research team should use these tools to identify stakeholder needs while also
233 considering the balance between the research goals and limitations of the data to meet these
234 goals. This approach will ensure that the needs of the management and stakeholder communities
235 will be consistent with the services provided by the research product.

236 An important practice that is not often used in bioassessment for project planning is study pre-
237 registration. This is a relatively new addition to the philosophy of open science that allows a
238 research team to define their study procedures, expected outcomes, and statistical analysis plans
239 in advance of the actual study (Munafó et al. 2017). Although the standard scientific method may
240 seem to support such proactive practices, pre-registration is an explicit declaration to make the
241 intentions of a study design clear to avoid publication bias where only positive outcomes are
242 reported and to prevent an interpretive result where the researcher retrospectively defines study
243 objectives after initial results are obtained if they do not agree with expectations. This latter issue
244 is a serious concern where scientists use postdiction with significant hindsight bias in place of
245 prediction and conventional hypothesis testing to inform scientific discovery (Nosek et al. 2018).
246 Registered reports can also be used as a publishing format where an initial study design is peer-
247 reviewed and the article is provisionally accepted by a journal if the results are created with
248 methods that do not deviate from the accepted design. This promotes greater coverage in the

249 primary literature of null conclusions that otherwise may not have been published, reducing bias
250 for publishing positive results.

251 Pre-registration has been used extensively in clinical research (Dickersin and Rennie 2003),
252 where outcomes often have immediate implications for human health and well-being. In contrast,
253 bioassessment studies often focus on developing applied products, where conventional
254 hypothesis testing is less a concern. Studies are typically methods-focused where a research
255 product is developed to address a management or regulatory need, rather than a specific research
256 question with a testable hypothesis. However, pre-registration could be an important tool for the
257 environmental sciences where an explicit declaration of study intent as being applied or
258 methods-focused could prevent postdiction or an otherwise misuse of study results after a project
259 is completed. Existing venues that support pre-registration of studies across multiple disciplines
260 could be used in bioassessment study planning (e.g., Open Science Framework, AsPredicted).

261 **Curating bioassessment data**

262 After project goals are established, the research team identifies requirements and sources of data
263 that need to be synthesized to meet the research needs. Bioassessment data, or more generally,
264 biological data obtained from field sampling have a unique set of challenges that require added
265 vigilance in data stewardship (Cao and Hawkins 2011). Species identification requires a tradeoff
266 between taxonomic specificity and cost (Lenat and Resh 2001, Chessman et al. 2007). Species
267 names also change regularly requiring updates to standard taxonomic effort (STE) tables that are
268 critical for many biological indices, although some standardized databases have facilitated broad-
269 scale comparisons (e.g., World Register of Marine Species, Costello et al. 2013). Unidentified or
270 ambiguous taxa must also be explicitly treated in analysis workflows (Cuffney et al. 2007), e.g.,
271 are they treated as missing values or are they substituted with coarser taxonomic designations? In
272 contrast, molecular techniques based on DNA barcoding eliminate the need for direct species
273 collection and morphological identification (Deiner et al. 2017, Hering et al. 2018). These next-
274 generation approaches have capitalized on advances in database development that allow open
275 access by diverse researchers across disciplines and are well-suited for the development of
276 additional open science tools. Despite these advances, molecular-based approaches have also
277 suffered from challenges related to standardization of workflows and coverage of reference
278 databases (White et al. 2014, Elbrecht et al. 2017).

279 Open science tools can facilitate the curation of bioassessment data by addressing the above
280 challenges. For example, a multimetric index may require taxonomic data collected at multiple
281 sites by different institutions, whereas the output data may include summary scores, individual
282 metrics, and any additional supporting information to assess the quality of the output. In an open
283 science workflow, these data products can be documented using a standardized metadata
284 language (e.g., Ecological Metadata Language Standard, or EML) which describes the who,
285 what, and why to ensure the data have an identity. Adoption of a metadata standard also ensures
286 that a machine-readable file is produced to allow integration into a data repository. This will
287 allow a synthesized data product to be discoverable beyond the specific research application and
288 will provide metadata to help others understand the context of the data (e.g., Idaszak et al. 2017).
289 Finally, the dataset can be assigned a unique digital object identifier (DOI, e.g., through Zenodo)
290 that provides a permanent address and is also citable to allow researchers to track usage of a
291 bioassessment data product.

292   In an open paradigm, the data itself is a product to achieve the research goals and also becomes
293   available to the research and management community as a fully documented source of
294   information that has value beyond the specific project. The openness of the synthesized data
295   product is one of the primary means of facilitating the application of a bioassessment product.
296   The synthesized data product can be used by the research team to create interactive applications
297   for stakeholders to share and explore the data and is also fully integrated into summary reports
298   using software for generating dynamic documents (e.g., using `knitr`, Xie 2015, RMarkdown,
299   Allaire et al. 2018, Jupyter notebooks, Kluyver et al. 2016). Continuous integration services can
300   automate quality control and regularly update data products as new information is collected
301   (Yenni et al. 2019). The data product also becomes available on an open data repository that is
302   discoverable by other researchers and can contribute to alternative scientific advances beyond the
303   immediate goals (e.g., Hydroshare for the hydrologic sciences, Idaszak et al. 2017).

304   **Using R for bioassessment application**

305   The R statistical programming language (RDCT 2018) is one of the most commonly used
306   analysis platforms in the environmental sciences (Lai et al. 2019, Slater et al. 2019) and many
307   existing R packages have value for the bioassessment community (Table 2). For managing the
308   day to day tasks of working with multiple datasets, the `tidyverse` suite of packages provides the
309   necessary tools to import, wrangle, explore, and plot almost any data type (Wickham 2017). The
310   `tidyverse` also includes the powerful `ggplot2` package that is based on a syntactical grammar
311   of graphics for plotting (Wilkinson 2005, Wickham 2009). This package provides a set of
312   independent plotting instructions that can be built piecewise and is a departure from other
313   graphics packages that represent a collection of special cases that limit the freedom of the
314   analyst. In bioassessment, `ggplot2` can be used both in an exploratory role during the
315   development phase and also to create publication quality graphics.

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

327   R is fundamentally a statistical language and several existing R packages can be used to evaluate
328   and support bioassessment data. Random forest models have been used to develop predictive
329   bioassessment indices that compare observed taxa to modeled expectations (i.e., O/E indices).
330   The `randomForest` package (Liaw and Wiener 2002) uses an ensemble learning approach that is
331   robust to complex, non-linear relationships and interactions between variables. These models are
332   particularly useful with large, regional datasets that describe natural and anthropogenic gradients
333   in condition (Laan and Hawkins 2014, Mazor et al. 2016). The `nlme` package can be used to
334   create non-linear mixed effect models that are more flexible than standard regression approaches
335   (Pinheiro et al. 2018). The `nlme` package can develop models for nested sampling designs, such

336 as repeat visits to sample sites or otherwise confounding variables that contribute information but
337 are not unique observations (Mazor et al. 2014). The `mgcv` package provides similar functionality
338 as `nlme`, but uses an additive modeling approach where individual effects can be evaluated as the
339 sum of smoothed terms (Wood 2017). The `mgcv` package is often applied to model biological
340 response to stressor gradients (Yuan 2004, Taylor et al. 2014).

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

354 Although the R network includes over 15000 user contributed packages, only a handful of these
355 packages are specific to bioassessment. Community practices have allowed R to reach new
356 audiences where new packages build on the work of others and are transportable between users
357 and operating systems. Formalized communities, such as rOpenSci, encourage standardization
358 and review of contributed packages within the ecological sciences to make scientific data
359 retrieval reproducible. Several tools have also been developed and published in the last five years
360 that greatly simplify the process of creating new packages in R (Wickham 2015, Wickham et al.
361 2018). The advantages of creating and sharing R packages that are specific to bioassessment
362 applications are important for several reasons. First, an R package compartmentalizes technical
363 instructions developed during the research phase that can be executed by anyone with access to
364 the software. R packages also require explicit documentation of the functions and data
365 requirements. As such, package users will not only have access to underlying code but also
366 understand the why and what for different package functions.

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

380 Open science in practice: The SCAPE project

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

394 Recent regulatory initiatives in California have established a foundation for openness that could
395 greatly improve the application of bioassessment products to support decision-making. In
396 particular, these initiatives have set a precedent for openly sharing data collected with public
397 funds. The Open and Transparent Water Data Act passed by the state legislature in 2016 requires
398 water quality institutions to "create, operate, and maintain a statewide integrated water data
399 platform that, among other things, would integrate existing water and ecological data information
400 from multiple databases and provide data on completed water transfers and exchanges" (AB
401 1755, Dodd, 2015-2016). This legislation also calls for state agencies to "develop protocols for
402 data sharing, documentation, quality control, public access, and promotion of open-source
403 platforms and decision support tools related to water data". These aspirations were further
404 supported by a resolution on July 10, 2018 that formally committed the State Water Resources
405 Control Board to "provide broader access to data used to make local, regional, and statewide
406 water management and regulatory decisions in California". These recent initiatives in California
407 have similarly been observed at the national level. For example, the Data Coalition is an
408 advocacy group that operates on behalf of the private and public sector for the publication of
409 government data in a standardized and open format. The Internet of Water also operates at the
410 national-level by focusing on strengthening connections between data producers and users
411 through centralized data hubs and data standards.

412 Open science tools have recently been used in California to address bioassessment
413 implementation challenges in developed landscapes. The Stream Classification and Priority
414 Explorer, or SCAPE (Beck 2018a, Beck et al. 2019), was developed using an open science
415 framework to help identify reasonable management goals for wadeable streams using existing
416 bioassessment and watershed data. The SCAPE tool represents both a modeling approach to help
417 prioritize management goals (Figure 3) and a set of open science products for direct application
418 to environmental managers. The modeling component addresses a practical problem of achieving
419 reference conditions in developed landscapes, where channel modification is common. Using the
420 National Hydrography Dataset (NHD-Plus; McKay et al. 2012) and watershed predictors
421 (StreamCat; Hill et al. 2016), the model classifies stream segments as biologically "constrained"
422 or "unconstrained" by landscape alteration. This classification system can be used to set
423 management priorities based on the constraint class. For example, a monitoring site with an

424 observed biological index score that is above a predicted range could be assigned a higher
425 management priority relative to a site that is scoring within the range that is expected based on
426 landscape development.

427 Open science tools were critically important for translating and delivering SCAPE products to
428 decision-makers. Local stakeholder engagement to identify research goals guided the technical
429 development process of SCAPE. All analyses, including model development and validation,
430 were conducted using R. A version control system (Git) and online hosting (GitHub) also
431 allowed full transparency of decisions that were made to create the SCAPE model. A permanent
432 DOI was assigned through Zenodo to track downloads and portability of source code (Beck
433 2018a). Importantly, an online, interactive web page (https://sccwrp.shinyapps.io/SCAPE)
434 greatly increased the impact and relevance of SCAPE by improving stakeholder understanding
435 through direct interaction with key decision points that influenced model output. A manuscript
436 describing the technical components of the model was created using knitr and RMarkdown (Xie
437 2015, Allaire et al. 2018). This increased efficiency of the writing process also minimized the
438 potential of introducing errors into tables or figures by eliminating the need to copy results
439 between different writing platforms. Finally, a geospatial data file from the model was also made
440 public on a federated data repository, which included metadata and plain language
441 documentation to track provenance of the original information (Beck 2018b).

Limitations and opportunities

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

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

465   Advocates of open science also recognize the limitations of teaching in that not all audiences can
466   be reached and not all materials are retained or even used after training. A strategy of
467   empowering trainees to become trainers and teach others at their home institutions (e.g., train-
468   the-trainer workshops and programs) enables open science to reach more individuals, and
469   benefits science more broadly as they develop technical and communication skills, and build
470   local communities. Those that also adopt new workflows through training can also direct their
471   research products to facilitate collaboration with non-adopters rather than the latter synthesizing
472   and analyzing their data in potentially suboptimal ways (Touchon and McCoy 2016). These
473   "champions" can be a voice of encouragement for others by demonstrating how new tools can be
474   introduced and learned over time through shared experiences (Lowndes et al. 2017). This also
475   encourages the development of a community of practice that shares and learns together to
476   navigate the collection of existing and developing open science tools (Stevens et al. 2018).
477   Champions of open science should also be vocal proponents that spread awareness of the value
478   of open science tools, particularly to those that make decisions on project resources. Department
479   heads or administrative leaders may not be aware of the value of investing in open science,
480   particularly if the consequences of not doing so are externalized in indirect costs that are not
481   budgeted. A change in mindset may be needed where open science is viewed as a core tool that
482   is critical to maintaining relevance of a research program in the future (Hampton et al. 2017).

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

501   The scientific culture within a discipline or institution may inhibit the adoption of open science
502   methods. A common argument against open science is the protection of data that an individual
503   research team may view as proprietary or sensitive. There are reasonable arguments to treat data
504   as personal property, particularly if exceptional effort was spent to secure funding for a project
505   and if the data were hard-earned or sensitive, e.g., detailed location data on endangered species
506   or medical/socioeconomic data (Zipper et al. 2019). These issues are less of a concern for
507   bioassessment where many datasets are collected by institutions that are publicly funded and data
508   accessibility may be mandated by law. However, an open science process dictates that both
509   interim and completed research products derived from public data should be available to the

510 broader bioassessment community. This raises an additional concern that research teams using
511 transparent workflows could expose themselves to increased criticism by their peers and the
512 public (Lewandowsky and Bishop 2016, Allen and Mehler 2019), particularly where the
513 developed products can have important regulatory implications.

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

530 Institutional barriers can inhibit open science given the scale of change that must occur for
531 adoption. Bureaucratic hurdles can disincentivize initiatives that promote change, particularly if
532 that change originates from researchers not in administrative roles. Regulatory institutions may
533 also prefer some level of opacity for how research products that influence policy are made
534 available during development. The level of transparency advocated by open science could be
535 viewed as opening the floodgates to increased legal scrutiny that can unintentionally hinder
536 forward progress. Despite these reservations, many public institutions now advocate for
537 increased openness because of the benefits that facilitate and engender public trust. Open data
538 initiatives are now fairly common and represent a form of advocacy by public institutions for
539 broader adoption of open science principles. Many national-level data products already exist that
540 embrace openness to invest in the quality and availability of data (e.g., National Water Quality
541 Monitoring Council initiatives, US Geological Survey products through NWIS and BioData, US
542 Environmental Protection Agency through STORET/WQX). Internationally, institutions in
543 Europe and Canada that have projects supported by public funds are obligated to publish data
544 and papers as open access (Horizon 2020, Tri-Agency Open Access Policy). Although past
545 efforts and recent changes represent progress, many institutions have yet to strictly define open
546 science and how it is applied internally and externally. As open science continues to build
547 recognition, means of integrating toolsets that promote openness and transparency beyond
548 publicly shared data will have to be adopted by regulatory and management institutions.

Conclusions

550 The relevance of bioassessment applications can be improved with open science by using
551 reproducible, transparent, and effective tools that bridge the gap between research and
552 management. Many open science tools can improve communication between researchers and

553   managers to expose all aspects of the research process and facilitate implementation to support
554   policy, regulation, or monitoring efforts. Communication ensures that the developed product is
555   created through an exchange of ideas to balance the potentially competing needs of different
556   sectors and institutions. The documentation and archiving of data used to create a bioassessment
557   product also ensures that other researchers can discover and build on past efforts, rather than
558   constantly rebuilding the wheel. Incremental improvements of existing products can reduce the
559   proliferation of site- and taxon-specific methods with limited regional applications by exploring
560   new ways to integrate biological indicators across space and time.

561   Efforts to formally recognize and integrate open science in bioassessment are needed now more
562   than ever. The transition of bioassessment from taxonomic-based indices to molecular
563   approaches presents novel challenges that will only increase in severity as researchers continue
564   to refine methods for molecular applications (Baird and Hajibabaei 2012). Although molecular-
565   based indices share similar assessment objectives as conventional indices, the data requirements
566   and taxonomic resolution are substantially more complex. Bioassessment researchers developing
567   molecular methods are and will continue to be inundated with data from high-throughput DNA
568   sequencers. Systematic approaches to document, catalog, and share this information will be
569   required to advance and standardize the science. Molecular approaches are also dependent on
570   existing reference libraries for matching DNA samples for taxonomic identification. The
571   integrity of reference libraries depends greatly on the quality of metadata and documentation for
572   contributed samples. Open science principles should be leveraged in this emerging arena to
573   ensure that new bioassessment methods continue to have relevance for determining the condition
574   of aquatic resources.

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Figure 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.

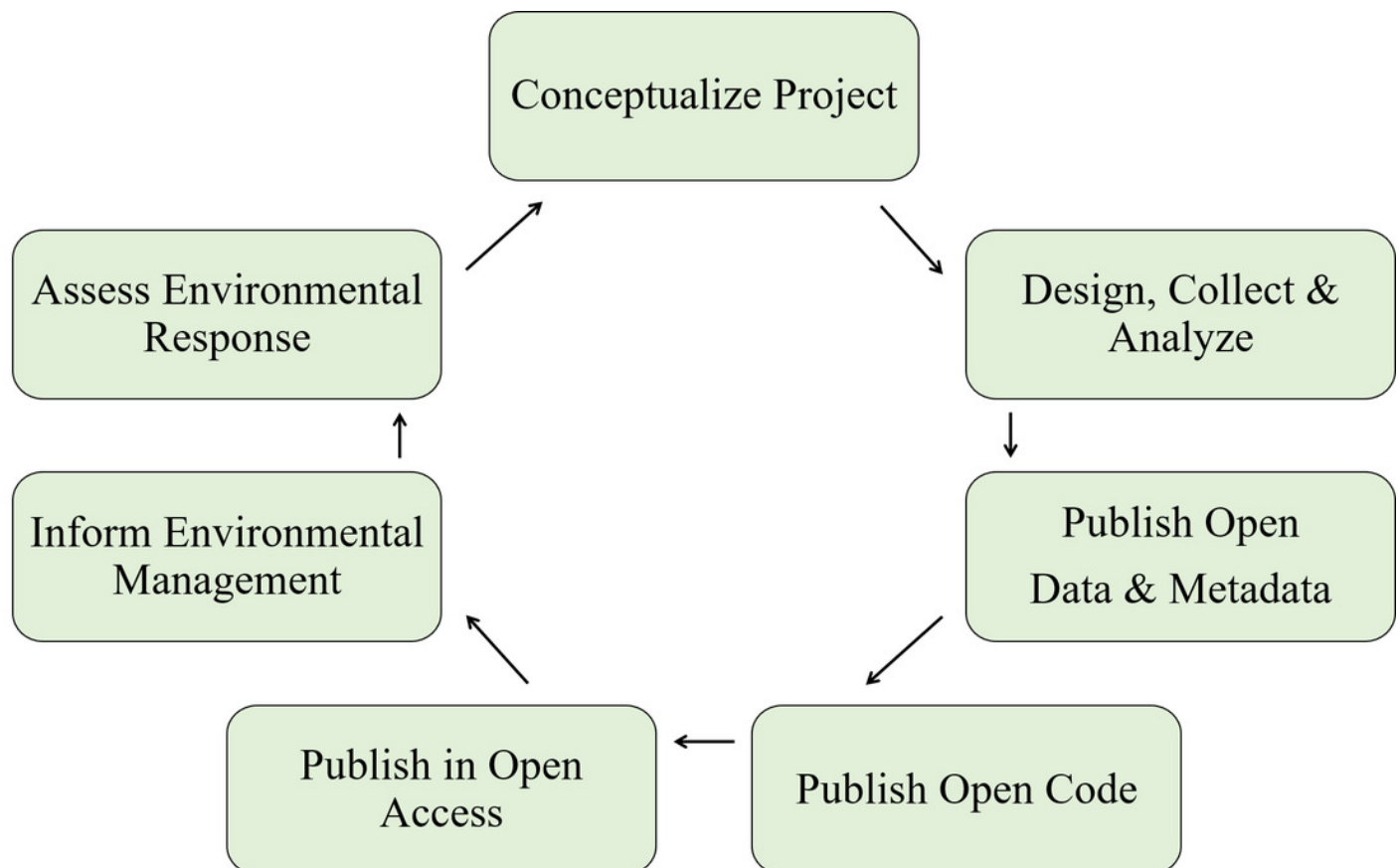



Figure 2

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.

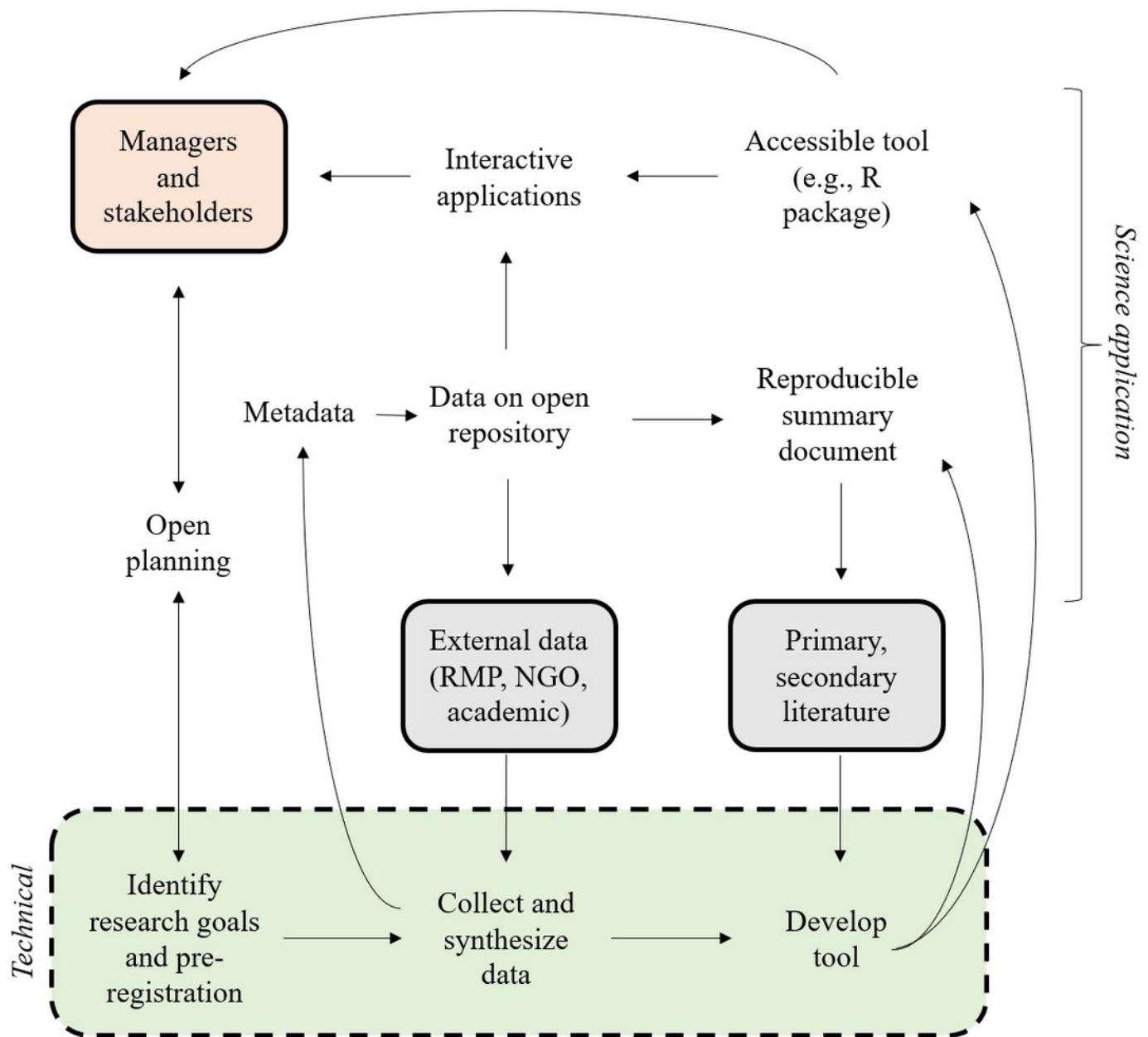



Figure 3

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 (A) 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 (B). Management actions and priorities can be defined based on site scores relative to segment classifications. TMDL: Total Maximum Daily Load. Photo credit: Raphael Mazor.

Site score

▽ under scoring   ○ expected   △ over scoring

Segment class

█ likely constrained   █ possibly unconstrained
█ possibly constrained   █ likely unconstrained

A

B

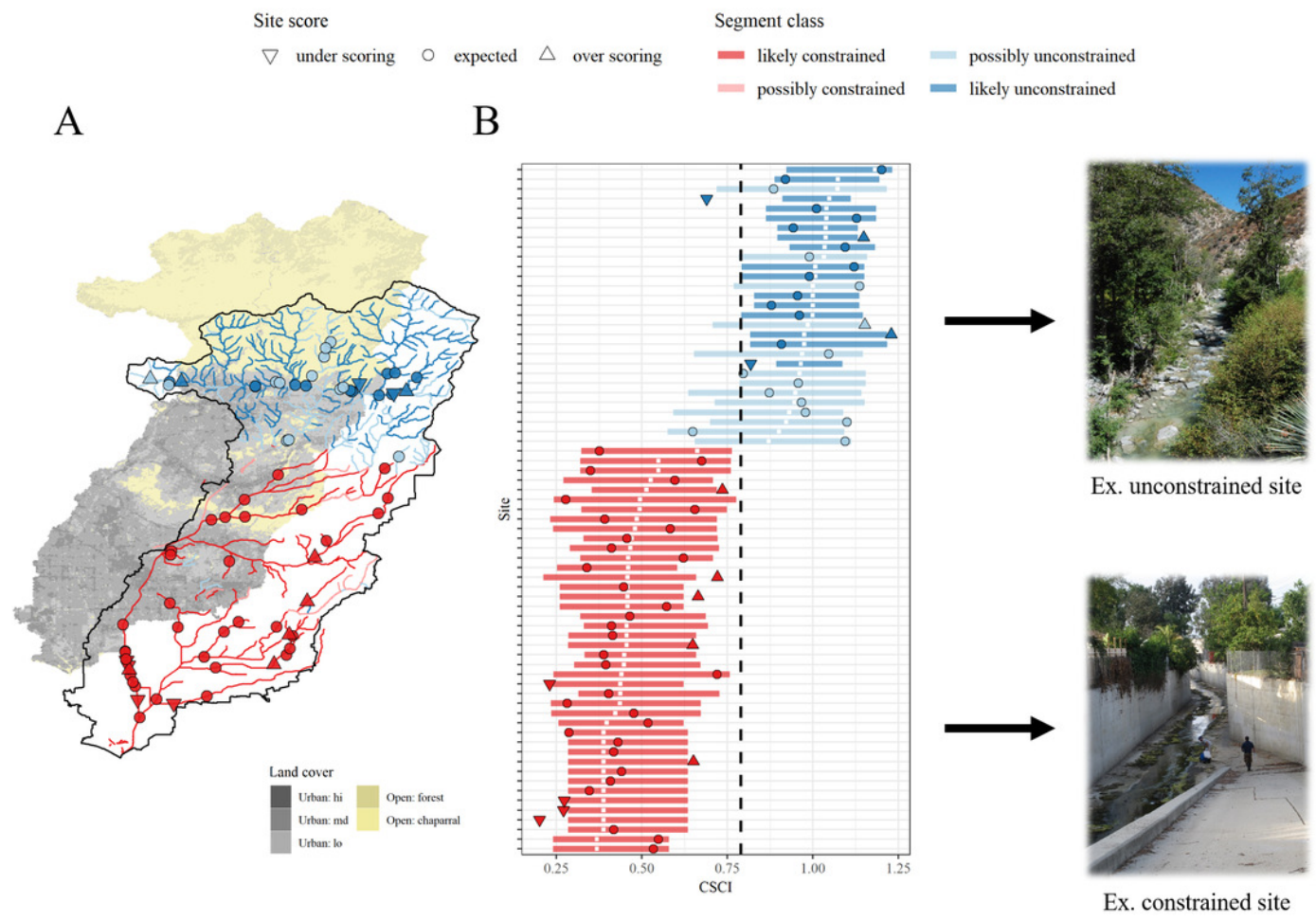
Land cover

Urban: hi   Open: forest
Urban: md   Open: chaparral
Urban: lo

CSCI

Site

Ex. unconstrained site

Ex. constrained site

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

Core definitions and principles of open science.

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Concepts and principles	Description
Open	Anyone can freely access, use, modify, and share for any purpose
Open Science	Practicing 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
Reproducible	Producing equivalent outcomes from the same data set, or in the case of computational reproducibility, producing equivalent outcomes from the same data set using the same code and software as the original study
Principle 1	Transparency in experimental methods, observations, and collection of data
Principle 2	Public availability and reusability of scientific data
Principle 3	Public accessibility and transparency of scientific communication
Principle 4	The use of web-based tools to facilitate scientific collaboration and reproducibility

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