The Stream Quality Index: A Multi-Indicator Tool for Enhancing Environmental Management Communication

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Southern California Coastal Water Research Project

May 2019
Technical Report ##

EXECUTIVE SUMMARY

Assessment of stream health is a function of the physical, chemical, and biological integrity of the water body. While monitoring of all three indicators of stream quality is commonplace, combining these three indicators into a unified assessment of stream quality is rare, complicating the interpretation of complex environmental health information. In this study, a unified index was developed that compares biological response to physical and chemical stressors for southern California wadeable streams using a scientifically rigorous, easy-to-understand tool intended to facilitate stream management. The Stream Quality Index (SQI) is based on a stressor-response empirical model that quantifies the expected likelihood that chemical and physical stressors will impact multiple individual components of biological condition. The index's chemical parameters, which are indicative of anthropogenic inputs, include nutrients and conductivity; the physical parameters include two physical habitat indices (Index of Physical Integrity, IPI; California Rapid Assessment Method, CRAM) that describe instream (i.e., substrate) condition and stream corridor (i.e., riparian) condition; and the biological response parameters include biological indices for benthic invertebrates and algae. While the individual stressor and response components are quantitative and have similar meaning across a variety of environmental settings, the final SQI narrative assessment is categorical and designed to be directly actionable within a management decision-making context. The four narrative assessment categories are: (1) "healthy and unstressed" (i.e., unimpacted biology, no physical or chemical stressors); (2) "healthy and resilient" (i.e., stressed, but biological communities are healthy); (3) "impacted and stressed" (i.e., impacted biology due to known chemistry and/or physical habitat stressor(s)); and (4) "impacted by unknown stress" (i.e., biology is impacted, but chemical and physical stressors are low). To facilitate adoption by managers, a web-based application was developed that not only maps overall SQI results, but also enables users to readily access underlying quantitative information for stressors and biological responses to understand likely reasons behind the categorical assessments. This transparent design was intended; high-level output and foundational components of the SQI are relevant for different audiences and details are not sacrificed for accessibility.

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INTRODUCTION

Assessments of stream health are a function of monitoring the water body's physical, chemical, and biological integrity (33 USC §§ 1251, 1972). Monitoring physical habitat integrity facilitates determination of whether all necessary environmental niches (e.g., hydrology, riparian structure, in-stream substrate) are present to support a diverse aquatic community (Maddock 1999). Monitoring chemical integrity facilitates determination of whether toxic compounds are present, as well as whether minerals are sufficiently balanced to support aquatic life (Maruya et al. 2016; Wang et al. 2007). Monitoring biological integrity, which is closest to the actual assessment of stream health, facilitates determination of whether unmeasured physical or chemical parameters are impacting otherwise balanced ecosystems (Ode et al. 2016; Stoddard et al. 2006), including any synergistic effects of measured and unmeasured parameters (Bowman et al. 2006).

Tremendous effort is expended to monitor all three types of stream integrity indicators. Despite varying spatial scales and complexities, all monitoring programs share the challenge of how to effectively communicate physical, chemical, and biological data in a scientifically rigorous, repeatable, and readily understandable way to non-scientists (National Research Council 1990). Because most environmental managers are not scientists, and similarly, scientists may not appreciate the applied context for technical products, the communication of ecological data for decision-making can be challenging. Furthermore, ecological data are rarely black and white, leading to many management decisions made in the "grey zone" (Paulsen et al. 2008). This is particularly true when physical, chemical, and biological indicators are not in complete agreement with one another.

Multiple well-known tools exist for effectively assessing and evaluating different components of stream condition. Bioassessment tools include the Index of Biological Integrity (IBI; Karr (1981)), Observed to Expected ratios (O/E; Hawkins et al. (2000)), and hybrids of the IBI and O/E (Mazor et al. 2016). Chemical assessment tools include the Canadian Council of Ministers of the Environment (CCME) Water Quality Index (CCME (Canadian Council of Ministers of the Environment) 2001; Hurley et al. 2012). Physical habitat assessment tools, which are less common, include the California Rapid Assessment Method (Collins et al. 2007; Solek et al. 2011) and the more recently developed Index of Physical Integrity (Rehn et al. 2018). These established tools are typically used to separately address chemical, physical, and biological components of the United States CWA.

An assessment tool that combines physical, chemical, and biological indicators into a single unified assessment is exceedingly rare (Bay and Weisberg 2012). Much more commonplace are instances where multiple indicators are individually simplified and presented as a group, leaving managers to decide which is most important (Paulsen et al. 2008). However, a single unified assessment is preferable when communicating stream health to non-technical managers. A single scale provides straightforward context for comparing one site to another, for ranking sites for management actions, and for monitoring improvements at a site following implementation of management actions (or monitoring potential degradation where management actions are not implemented).

While such a unified assessment tool is possible to develop for use in a single environmental setting, it has long been a challenge to design a technically robust tool that produces assessments that have similar meanings in different environmental settings, that provides clues as to which stressor(s) is/are impacting biological indicator(s), and that can be replicated elsewhere. The goal of this study was to develop a tool that meets all three criteria. Because biological indicators provide direct measures of aquatic life, while physical and chemical measures provide ancillary information about the stressors that may affect aquatic life, this study sought to develop a method for combining the three indicators in a way that would preserve the types of information provided by each. This is fundamentally different than treating indicators as equivalent and simply "averaging" results to assess overall condition.

METHODS

General Approach

The conceptual approach used in this study is based on a stressor-response relationship between biology and the stream environment (Figure 1). Specifically, the underlying stressor-response relationships that define the final narrative categories for overall stream condition are based on empirical models that quantify an expected likelihood of chemical or physical stressors impacting the separate components of biological condition. Southern California wadeable streams were selected as the focus of this effort because of the extensive and varied levels of stress and biological impacts. Moreover, southern California is home to many environmental managers with a variety of backgrounds and experience in technical and policy issues.

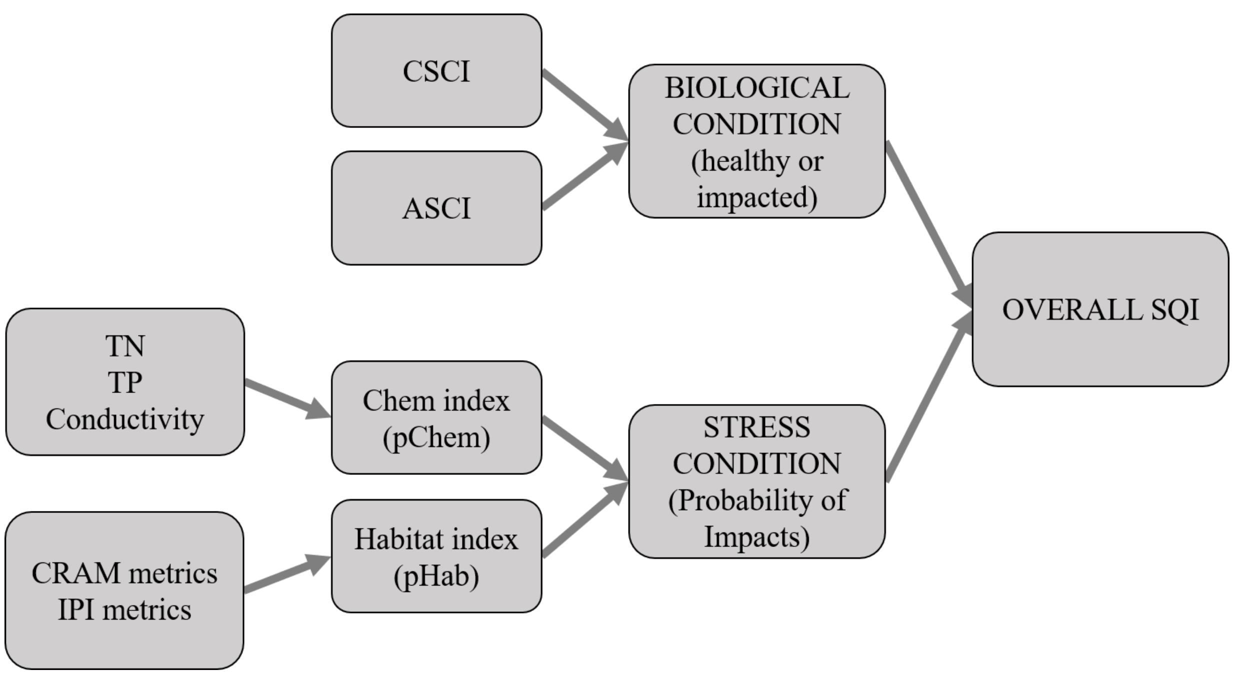

Figure 1. Flowchart representation of the Stream Quality Index (SQI). The overall SQI is a function of the likelihood of observing degraded biological condition given the stressors at a site. Biological condition is assessed using macroinvertebrate (California Stream Condition Index, CSCI) and algal (Algal Stream Condition Index, ASCI) indices and stressors are evaluated based on water quality measures (total nitrogen, total phosphorus, conductivity) and physical habitat (California Rapid Assessment Method, CRAM; Index of Physical Integrity, IPI). Stress condition is empirically linked to biological condition by separate probability functions for chemistry (pChem) and physical habitat (pHab).

Biological response components were selected based on bioassessment indices developed for California wadeable streams (i.e., benthic macroinvertebrates, algae). Water chemistry stressors were selected that are strongly associated with biological condition in perennial streams (i.e., nutrients, conductivity). Physical habitat indices were selected that quantify flow, channel, and riparian condition observed at a site. Specific justification for the chosen stressors and their relationship to biology is described below. In short, the conceptual stressor-response model reflected by our choice of indicators is generally described as the habitat requirements for biological organisms and the alteration (i.e., response) in the structure and function of these communities along stressor gradients as habitat quality declines. These relationships establish the foundation of many bioassessment methods (Karr 1981; Karr and Chu 1999; Stoddard et al. 2006) and our stressor-response model reflects these principles.

The four narrative assessment categories were defined in a way that would align with management processes. The SQI web-based application was designed in a way that would give users easy access to descriptions of the biological, chemical, and physical components that underlie the unified assessment, depending on the desired level of information within the stressor-response paradigm.

Biological response components of the SQI

Characterizing biological condition

To characterize biological condition, a pair of quantitative bioassessment indices – for benthic macroinvertebrates (BMI) and algal communities, respectively – were used that have been developed for California streams (Mazor et al. 2016; Theroux et al. n.d.); the indices were treated as complementary assessment tools in the SQI.

The California Stream Condition Index (CSCI, Mazor et al. (2016)) is a predictive index that compares observed benthic macroinvertebrate taxa and metrics at a site to those expected under least disturbed reference conditions (sensu Stoddard et al. (2006)). Expected values at a site are based on models that estimate the likely macroinvertebrate community relative to factors that naturally influence biology (Cao et al. 2007; Moss et al. 1987).

The Algal Stream Condition Index (ASCI, Theroux et al. (n.d.)) was similarly developed as a response endpoint for lower trophic levels; the ASCI is a non-predictive multi-metric index (i.e., it uses a uniform, statewide reference expectation) that incorporates both diatoms and soft-bodied algae. Scores for both indices can range from 0 to ~ 1.4, with a score of 1 at sites in reference condition and lower values indicating biological degradation. Both communities are used as standard assessment measures for perennial wadeable streams in California.

Index scores were compared to the distribution of scores at reference sites statewide to identify biological condition classes that described the likelihood of biological alteration. For both the CSCI and ASCI, the 1st, 10th, and 30th percentiles of scores at reference sites were used to categorize sites as very likely to have altered biological condition (scores less than the 1st percentile), likely altered (scores between the 1st and 10th percentile), possibly altered (scores between the 10th and 30th percentiles), and likely intact (scores greater than the 30th percentile) (Table 1). This produced four classes for each index, such that each site had two categories describing separate indications of the likelihood of biological alteration in the benthic macroinvertebrate and algal communities. Both response endpoints were jointly considered in the calculation of the SQI for evaluating overall biological condition, described below. Analysis of multiple assemblages provides a more comprehensive indication of biological condition that can confirm overall stream health, and may also provide additional diagnostic information about stressors (as different communities may respond to different characteristics of stream habitat).

Integrating multiple measures of biological condition

The assigned biological condition categories for each index were combined using a ranking system to create a single numeric value that represented an overall condition reflected by both biological indices. A technical advisory committee with representatives from local management institutions provided guidance on assigning these values in accordance with two principles. First, the two indices should be independently applicable, so that an indication of good health in one index cannot negate indications of poor health in the other. Second, the numeric values should be sensitive to differences between sites in marginal or extreme conditions. For example, the numeric value for a sample where both indices indicate likely intact biological communities will be higher than for a sample where one index indicates likely intact and the other indicates possibly altered. This sensitivity improves detection of small changes in condition. The final numeric values ranged from -6 to +5 (Table 1). All negative values indicate impacted conditions.

Table 1. Combined biological condition categories for the benthic macroinvertebrate (BMI) and algal indices. The combined categories were used to model the likelihood of biological alteration given observed physical and chemical habitat stressors. Sites with combined categories greater than or equal to zero were considered biologically healthy and those less than zero (in bold) were considered biologically impacted (i.e., response variable in equations (1) and (2)). Individual biological categories for the BMI and algal indices were based on percentile distributions of scores at reference sites (i.e., 1st, 10th, and 30th percentiles) as likely intact (> 30th), possibly altered (10th - 30th), likely altered (1st - 10th), and very likely altered (< 10th). The scores associated with the percentiles for each index (CSCI, ASCI) are in parentheses.

	Algae likely intact: (ASCI > 0.93)	Algae possibly altered: (ASCI 0.83 - 0.93)	Algae likely altered: (ASCI 0.70 - 0.83)	Algae very likely altered: (ASCI < 0.70)
BMI likely intact: (CSCI > 0.92)	5	3	**-1**	**-2**
BMI possibly altered: (CSCI 0.79 - 0.92)	3	2	**-2**	**-4**
BMI likely altered: (CSCI 0.63 - 0.79)	**-1**	**-2**	**-3**	**-5**
BMI very likely altered: (CSCI < 0.63)	**-2**	**-4**	**-5**	**-6**

Stressor components

Characterizing stress

Water chemistry and physical habitat measurements, which were used to describe stressors associated with low CSCI and ASCI scores (Mazor 2015; Theroux et al. n.d.), are strongly linked to the structure and function of both invertebrate and algal assemblages (Pan et al. 2002; Richards et al. 1997; Wang et al. 2007). Depending on the context, physical habitat can be considered a response metric of stream health. However, physical habitat herein is considered a stressor that can affect biological condition at different taxonomic levels within the stressor-response model.

The water chemistry indicators consisted of nutrients - specifically, total nitrogen (mg/L) and total phosphorus (mg/L) - and specific conductivity (μS/cm). Nitrogen, phosphorus, and conductivity are widely measured in many regional and statewide monitoring programs. These variables are commonly associated with development gradients present in the study region (e.g., urbanization, Dodds et al. (2002), Walsh et al. (2005)). Additionally, these variables can act as surrogates for unmeasured or alternative water quality problems at a site related to eutrophication (e.g., temperature, light penetration, Dodds and Smith (2016)). Although other contaminants that can affect aquatic organisms are sometimes measured (e.g., metals, pesticides, pharmaceuticals), observations can be sparsely distributed in the study region (Mazor 2015). Eutrophication is a more ubiquitous issue in the study region, although we acknowledge that other stressors not captured by the SQI may affect biological condition.

Physical habitat conditions at a site were quantified using two indices of habitat condition developed for California water bodies: the Index of Physical-Habitat Integrity (IPI; Rehn et al. (2018)) and the California Rapid Assessment Method (CRAM) for riverine wetlands (Collins et al. 2007; Solek et al. 2011). Although IPI and CRAM scores can be correlated, the individual metrics that establish each index provide unique information about speciic components of the physical habitat. Moreover, IPI scores specifically describe instream condition, whereas CRAM scores describe riparian condition.

The IPI is an O/E index (Hawkins et al. 2000) based on physical habitat metrics (PHAB, (Rehn et al. 2018)) that collectively characterize five components of in-stream habitat quality: percent sands, fines, or concrete, Shannon diversity of aquatic habitat types, Shannon diversity of natural substrate types, evenness of flow habitat types, and riparian vegetation cover. All five metrics are positively associated with physical habitat integrity, such that an increase in each was generally considered an improvement in site condition (percent sands and fines is inversely scored). All physical data used to calculate these metrics were collected using standard field protocols described in Ode (2007), which are derived from protocols used in national assessments (USEPA (U.S. Environmental Protection Agency) 2016). As with the CSCI, the IPI is a predictive index, and values for most metrics are compared to site-specific expectations appropriate for the stream's environmental setting. The IPI ranges from 0 to ~1.4, with values less than 1 indicating departure from reference conditions.

In contrast to the IPI, CRAM is based on qualitative assessments of four attributes of riparian wetland function: landscape and buffer condition, hydrologic condition, physical structure, and biotic structure. Whereas the data for the IPI is derived from numerous quantitative measurements of physical habitat components collected along several transects, CRAM attributes are assessed on a whole-reach scale through visual observation. In general, CRAM characterizes larger-scale processes affecting stream condition both within and adjacent to the stream corridor, whereas the IPI focuses more narrowly on in-stream conditions. CRAM scores range from 25 to 100, with higher values indicating less degraded conditions at a site.

Integrating multiple measures of stress

The combined impact of habitat or chemistry stressors on biological condition was evaluated by developing stress-response models that calculate the probability of observing poor biological conditions given observed levels of chemical or habitat stress. This approach eliminates the need to identify potential thresholds for identifying high levels of stress while also accounting for their combined impacts.

For both types of stress, a generalized linear model (Fox and Weisberg 2011) was fit to calibration data for Southern California streams to quantify associations for each separate water quality or physical habitat measure with binomial categories for altered or unaltered biology. Two models were developed:

$$pChem: p(bio) \sim \beta_0 + \beta_1 TN + \beta_2 TP + \beta_3 cond \qquad (1)$$

$$pHab: p(bio) \sim \beta_0 + \beta_1 CRAM_{blc} + \beta_2 CRAM_{ps} + \beta_3 IPI_{PCT\_SAFN} \qquad (2)$$

where $p(bio)$ is the probability of biological alteration in equations (1) and (2) given the indicators for each chemistry or physical habitat variable. The probability of alteration is modelled using a logit link function for binomial variables, as $log\left(p/(1-p)\right)$, where p defines the presence or absence of altered biology described above. Both models were created by screening collinear predictors by removing those with variance inflation factors (VIF) greater than three (Zuur et al. 2007). The most parsimonious model was then identified using backward and forward selection to minimize Akaike Information Criterion (Akaike 1973; Venables and Ripley 2002). The selected variables for each model are shown above (equation (1), TN: total nitrogen, TP: total phosphorus, cond: specific conductivity; equation (2), CRAM_{blc}: CRAM buffer landscape condition, CRAM_{ps}: CRAM physical structure, IPI_{PCT_SAFN}: IPI % sands and fines).

An overall likelihood of biological alteration from both chemistry and physical habitat stressors was also estimated as a multiplicative function for $pChem$ and $pHab$:

$$pOverall: p(bio) \sim 1 - \left((1 - pChem) \times (1 - pHab)\right) \qquad (3)$$

The inverse of the likelihoods was used to represent an additive effect of both chemistry and physical habitat stressors. Equations (1), (2), and (3) provided the empirical estimates of biological alteration that were used to define the categorical outputs of the SQI, defined below.

Combining stress and response measures into the final SQI assessment

The empirical framework for the binomial models and combined biological condition categories established a basis for the categorical descriptions from the SQI output. These descriptions linked the quantitative data to management actions, such that the results were easily interpreted with an indication of biological condition and the relevant stressors which may or may not be related to condition. For the components in Figure 1, categorical outputs are provided by the index for the overall SQI, the biological condition, and the stress condition (Figure 2). The categorical outputs were created from a matrix combination of the respective inputs.

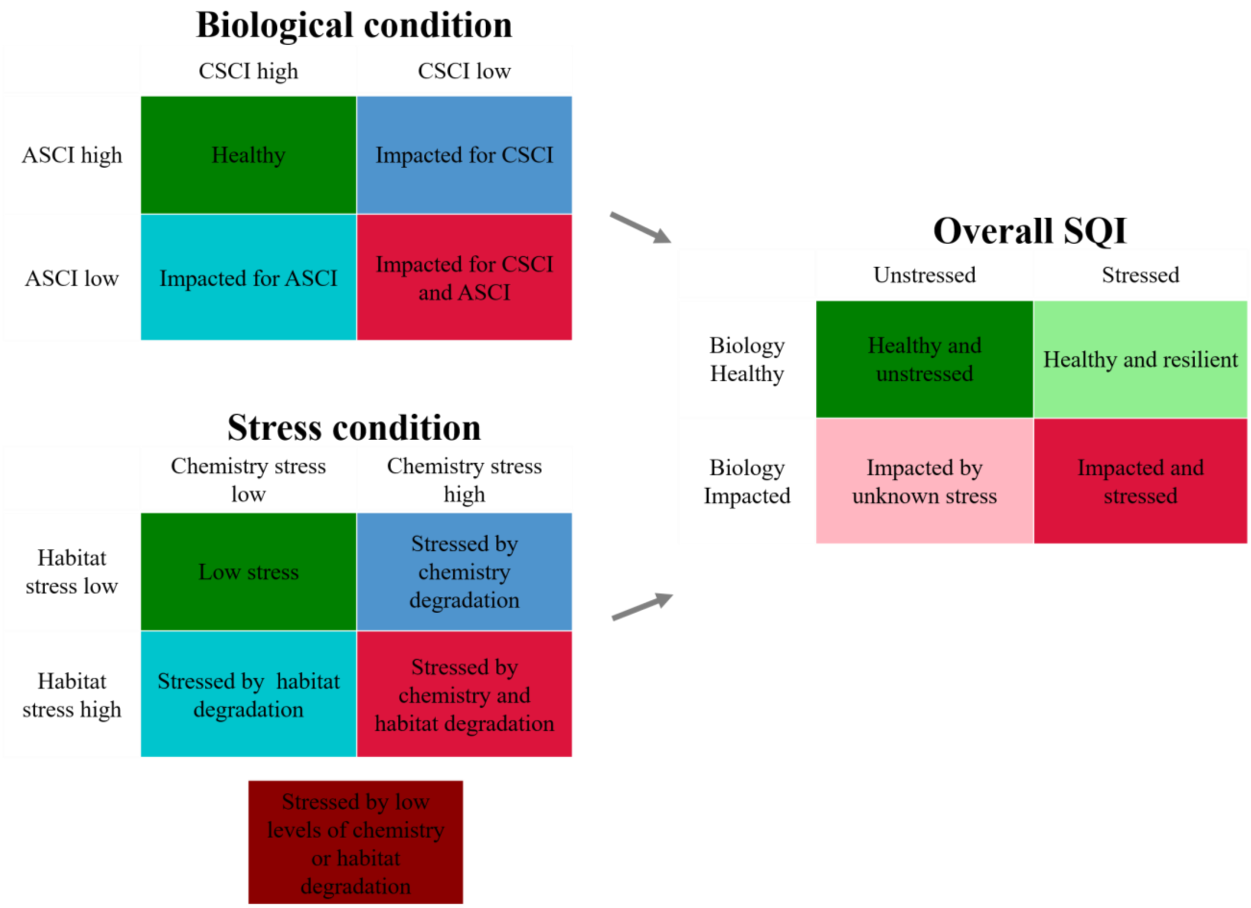

Figure 2. Categorical site descriptions that are possible from the Stream Quality Index (SQI). The overall SQI is described as the possible outcomes from biological and stress conditions. The biological conditions are described by the possible outcomes from the CSCI and ASCI. The stress conditions are described by the possible outcomes from the chemistry and habitat stressors. A fifth stress category is possible because stress from both chemistry and habitat was multiplicative.

The overall SQI assessment categories describe four possible combinations of biology and stressors at a site from the binary categories of altered/unaltered biology and stressed/unstressed conditions: (1) healthy and unstressed, (2) healthy and resilient, (3) impacted by unknown stress, and (4) impacted and stressed.

Separate categorical outputs were also created for the biological condition and stressor condition categories. The four possible outputs for the biological categories were based on the four combinations from the combinations of high/low CSCI and high/low ASCI: (1) healthy, (2) impacted for CSCI, (3) impacted for ASCI, and (4) impacted for both. The possible stressor condition categories for a site were based on the four outcomes of the combinations of high/low chemistry stress and high/low physical habitat stress: (1) low stress, (2) stressed by chemistry, (3) stressed by habitat, (4) stressed by both, and (5) stressed by low levels of chemistry and physical stress. The fifth stress category was possible based on the additive effects of both stressors when both were low (i.e., if $pOverall$ exceeded the threshold even though $pChem$ and $pHab$ did not).

Thresholds for biological indices that defined altered/unaltered condition for the SQI categories were based on the tenth percentile distribution of scores at reference sites for each index. Thresholds for high/low stress categories were based on a 90% likelihood of observing a biological impact from the empirical models. The stress threshold was identified by a technical advisory group and was chosen to provide a relatively even distribution of sites in the high/low stress categories. The threshold is reflective of the distribution of observations in the calibration dataset that had many sites in poor biological condition and was chosen strictly to create a more balanced distribution of stress categories. Alternative thresholds should be used when applying the model in regions with different or diminished stressor gradients.

Finally, the use of a predictive model to identify healthy/impacted biology and the use of biology as a component of the index (i.e., the categorical outputs) may seem circular. However, we note that the empirical models in equations (1), (2), and (3) define the likelihood of alteration that relates stress to biology to define the overall SQI output (e.g., healthy and impacted). The biological categories as a component of the index are the modelled response endpoints in the models, but also serve as standalone endpoints that describe biological condition in the absence of the stressor-response model.

Calibration and validation of the SQI

All data used to calibrate and validate the SQI were from the Southern California Stormwater Monitoring Coalition (SMC) regional watershed monitoring program in coastal southern California (Mazor 2015, Figure 3). The SMC dataset represents the most comprehensive source of wadeable stream data in southern California. Because the SQI requires synoptic biological, chemistry, and physical habitat data, the final dataset used for model calibration represents only the subset of the SMC dataset where all three components were simultaneously collected. Made up of 266 sites – 75% of which were used for model calibration – this subset includes sampling dates ranging from 2009 to 2016, with relatively even distribution of samples between years. Most sample events occurred between May and June following standard protocols for perennial stream surveys (Ode 2007). Only one sample event for each site was considered.

The SQI was evaluated for precision (i.e., how well the underlying empirical model described the likelihood of biological alteration) and sensitivity (i.e., how sensitive the model output is to changing thresholds that define the categorical conditions). The first analysis evaluated precision in the validation dataset to determine agreement between the model and actual stress and biological conditions. For the second analysis, two critical decision points that affected the model output and categorical results of the SQI were varied to evaluate changes on overall site counts in each final SQI category. In Table 1, all sites with combined values greater than or equal to zero were considered healthy and those less than zero were considered impacted. The effect of varying the cutoff point for healthy and impacted biology was analyzed by comparing changes in the SQI assessment categories at different levels from -6 (all healthy) to 6 (all unhealthy). Changes in the threshold for the likelihood of observing altered biology that defined the categorical results were also evaluated.

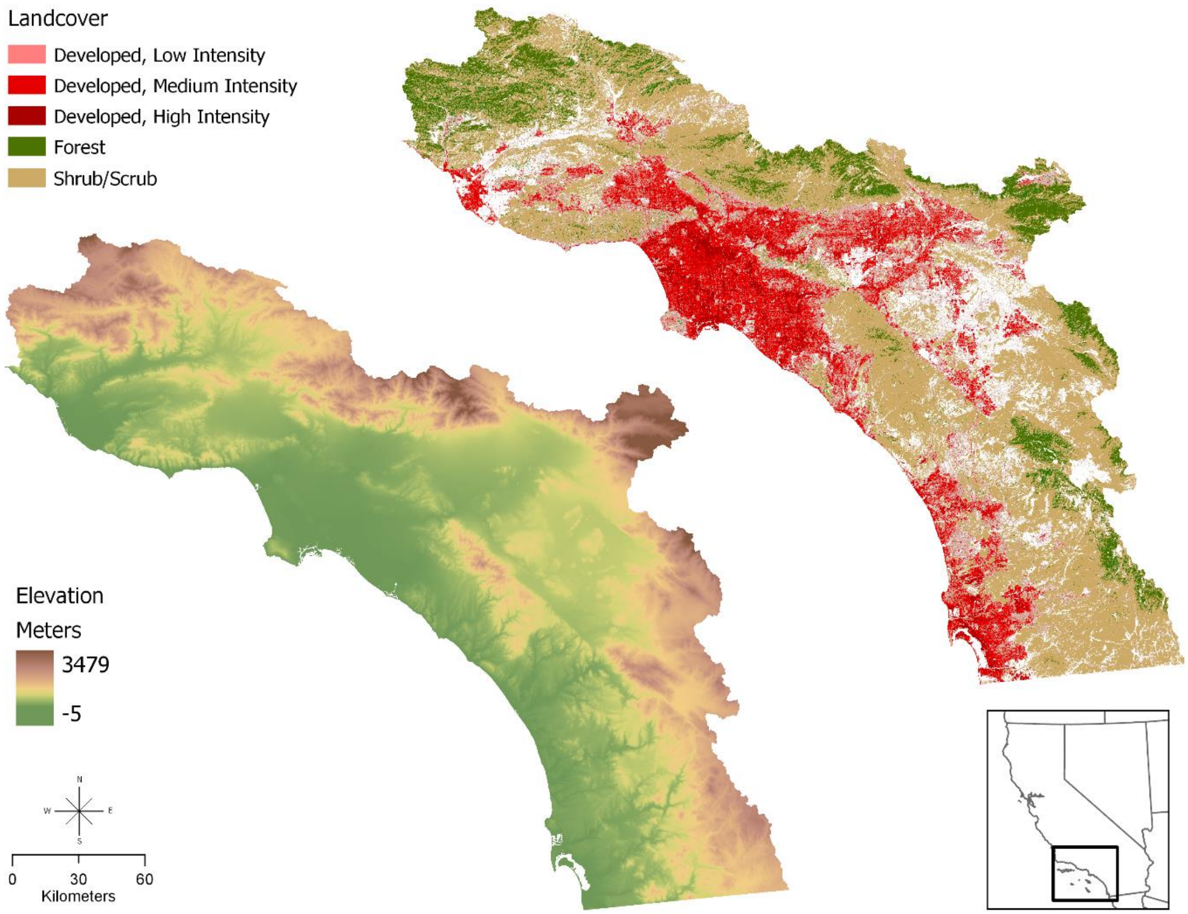

Figure 3. Land cover and elevation gradients in the study region in southern California, USA

Selected case studies

SQI results for two examples were explored in detail to provide a narrative description of how the index can be used to inform management of water quality in perennial streams. The first example describes SQI results in an urban channel with impacted biology (County of Orange) to complement a previous causal assessment study to identify potential stressors of low CSCI scores. The second example describes a natural channel with impacted biology but low stress that is highlighted in a draft regional basin plan for biological objectives for the San Diego region. Both examples demonstrate how the SQI can be used in the context of existing, site-specific information to support management.

RESULTS

SQI patterns

Among all sites, the overall SQI categorized a majority of sites as having altered biology under high stress conditions (impacted and stressed, 71% of sites, Table 2). Almost 20% of sites were in the opposite category of unaltered biology in low stress conditions (healthy and unstressed).

For the remaining two categories of the overall SQI, only 3% had unaltered biology but were under high stress conditions (healthy and resilient), whereas 6% sites had altered biology not related to physical or chemical stressors (impacted by unknown stress).

Table 2. Counts of sites in each of the categorical outputs from the SQI. For every SQI output (biological condition, overall SQI, stress condition), a site is categorized as one of four possible outcomes.

SQI output	Category	Count (percent)
Overall SQI	Healthy and unstressed	51 (19.1)
	Healthy and resilient	9 (3.4)
	Impacted and stressed	189 (70.8)
	Impacted by unknown stress	18 (6.7)
Biological condition	Healthy	60 (22.5)
	Impacted for ASCI	43 (16.1)
	Impacted for CSCI	30 (11.2)
	Impacted for CSCI and ASCI	134 (50.2)
Stress condition	Low stress	69 (25.8)
	Stressed by chemistry and habitat degradation	107 (40.1)
	Stressed by chemistry degradation	56 (21)
	Stressed by habitat degradation	13 (4.9)
	Stressed by low levels of chemistry or habitat degradation	22 (8.2)

For the biological condition category, sites with altered conditions were more often altered for both CSCI and ASCI scores (50%) than the other categories (i.e., altered for only one index). For sites with one low-scoring index, more sites were altered for the ASCI (16%) than the CSCI (11%). Less than a quarter of all sites had unaltered biology (23%).

For stress conditions, 40% of sites were stressed by both chemistry and physical habitat stressors. More sites were stressed by water chemistry (22%) than physical habitat degradation (5%) if only one stressor was present. Over 25% of sites had low stress, and 8% of sites were stressed by the additive effect of both low chemistry and physical habitat stressors.

Spatial patterns among SQI categories in southern California generally followed elevation and land use gradients (Figures 3, 4). More altered biological communities and high stress conditions were observed toward coastal areas at lower elevation where urbanization is highest (e.g., Los Angeles, Orange County, Ventura, San Diego). Sites with altered biological condition showed similar spatial patterns as the overall SQI, although sites altered only for the ASCI were more often observed at mid-elevation across the study region, whereas sites altered only for the CSCI were more common at higher elevation areas in central and northern areas of the study region. Stress condition patterns were similar to biology, although low stress conditions also occurred at higher elevation areas in each watershed. This produced a handful of sites that had altered biology under low stress conditions at mid-elevation ranges (i.e., impacted by unknown stress, Table 2).

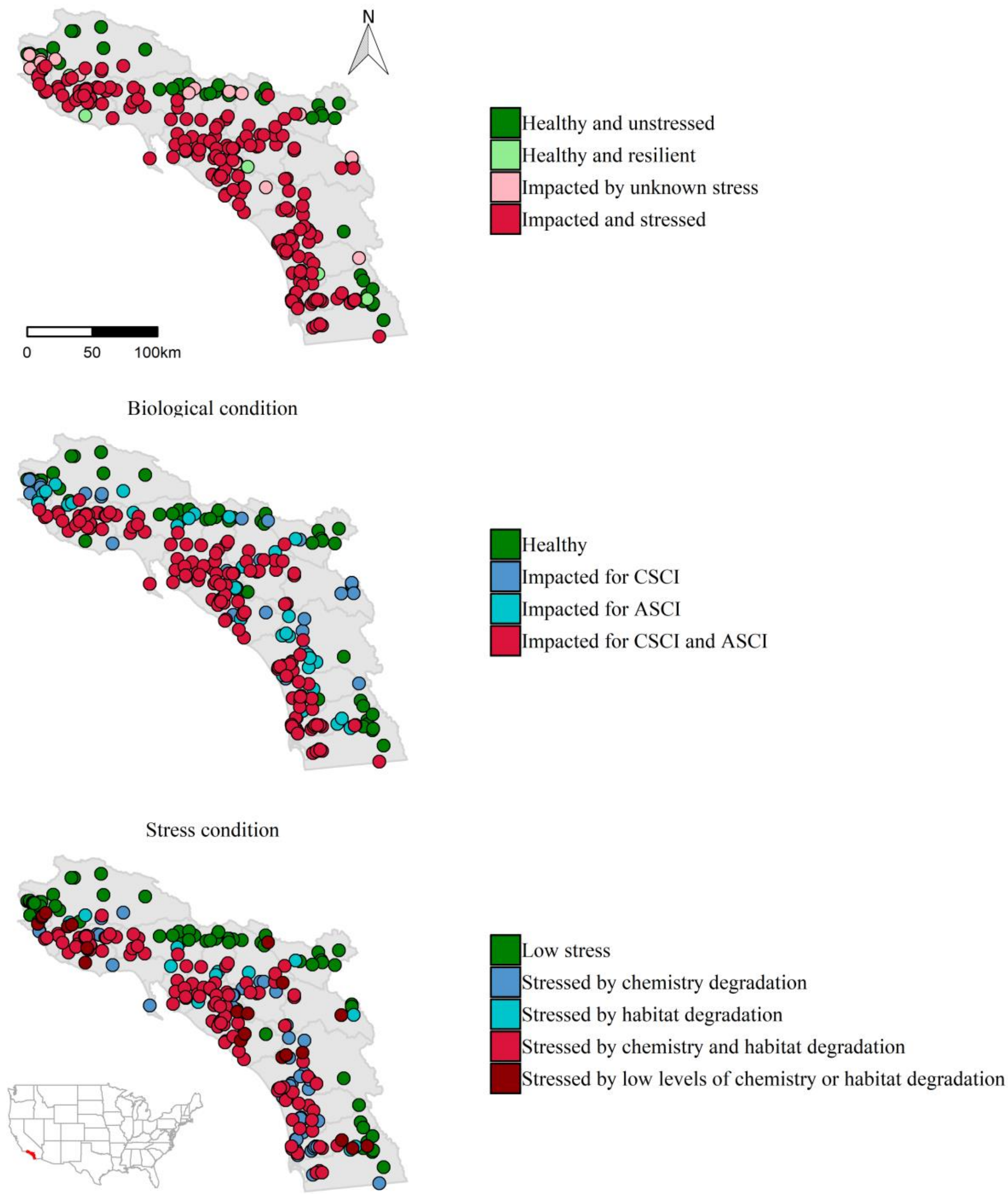

Figure 4. Categorical site descriptions for the Stream Quality Index (SQI) at monitoring sites in Southern California. The overall SQI (top) is described as the possible outcomes from biological (middle) and stress conditions (bottom). The biological conditions are described by the possible outcomes from the CSCI and ASCI. The stress conditions are described by the possible outcomes from the chemistry and habitat stressors.

Model precision

The distinction between healthy and impacted biological communities was well-described by the estimated likelihood of biological alteration provided by the empirical models (Figure 5). Relatively good separation was observed between sites designated as healthy or impacted in the validation (dark grey boxes) data for the three stressor-response models. Slightly larger differences between the likelihood of alteration for healthy and impacted communities were observed for the chemistry model compared to the physical habitat model, suggesting an improved fit for the former (for healthy/impacted communities at validation sites, t = 5.89, df = 19.09, $p < 0.001$ for *pChem*; t = 6.26, df = 26.51, $p < 0.001$ for *pHab*). For the overall likelihood of biological alteration (*pOverall*), more sites were greater than 90% likely to be altered in the impacted category as compared to the separate *pChem* and *pHab* models. For all cases (*pChem*, *pHab*, *pOverall*), there were no systematic differences in model results between calibration and validation datasets both qualitatively (similar distribution in the boxplots) and quantitatively ($p > 0.05$ for the interaction and fixed effect of site type in linear models describing likelihood of alteration between impact categories and site type).

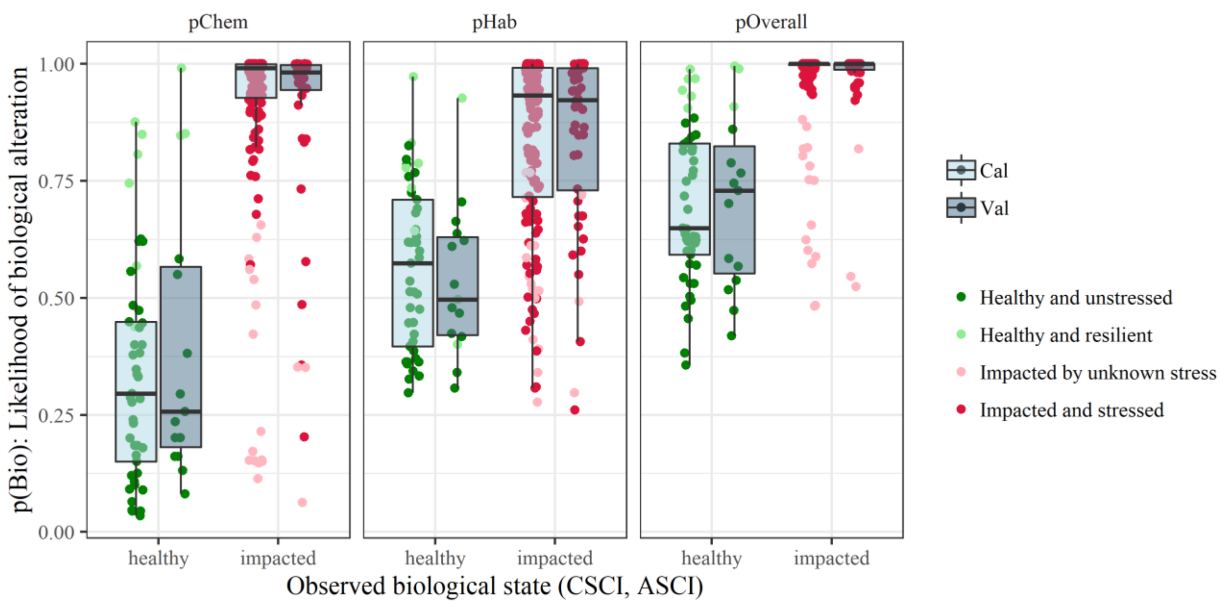

Figure 5. Boxplot distributions of the modelled likelihood of biological alteration relative to water chemistry (pChem, eqn. (1)) and physical habitat variables (pHab, eqn. (2)) and the additive overall stress as the product between the two (pOverall, eqn. (3)). Groups are separated into healthy or impacted biological condition at each site (Table 1) as the response measure for each model and by calibration/validation datasets (3:1 split). Model precision can be evaluated by comparing the differences between the boxplots for the validation data for healthy and impacted categories, whereas model bias can be assessed by comparing the distributions between calibration and validation data among biological state and models. Points show the four possible categorical outcomes from the overall SQI. CSCI: California Stream Condition Index, ASCI: Algal Stream Condition Index.

The underlying empirical models provided insight into instream characteristics that were related to the likelihood of biological alteration (Figures 6, 7). About 77% of sites (n = 205) had greater than 50% likelihood of biological alteration from water chemistry stressors, and 84% (n = 224) had greater than 50% likelihood of biological alteration from physical habitat stressors (Figure 6). Collectively, 97% (n = 258) of sites had greater than 50% likelihood of biological alteration from the overall stress of both chemistry and physical habitat stressors.

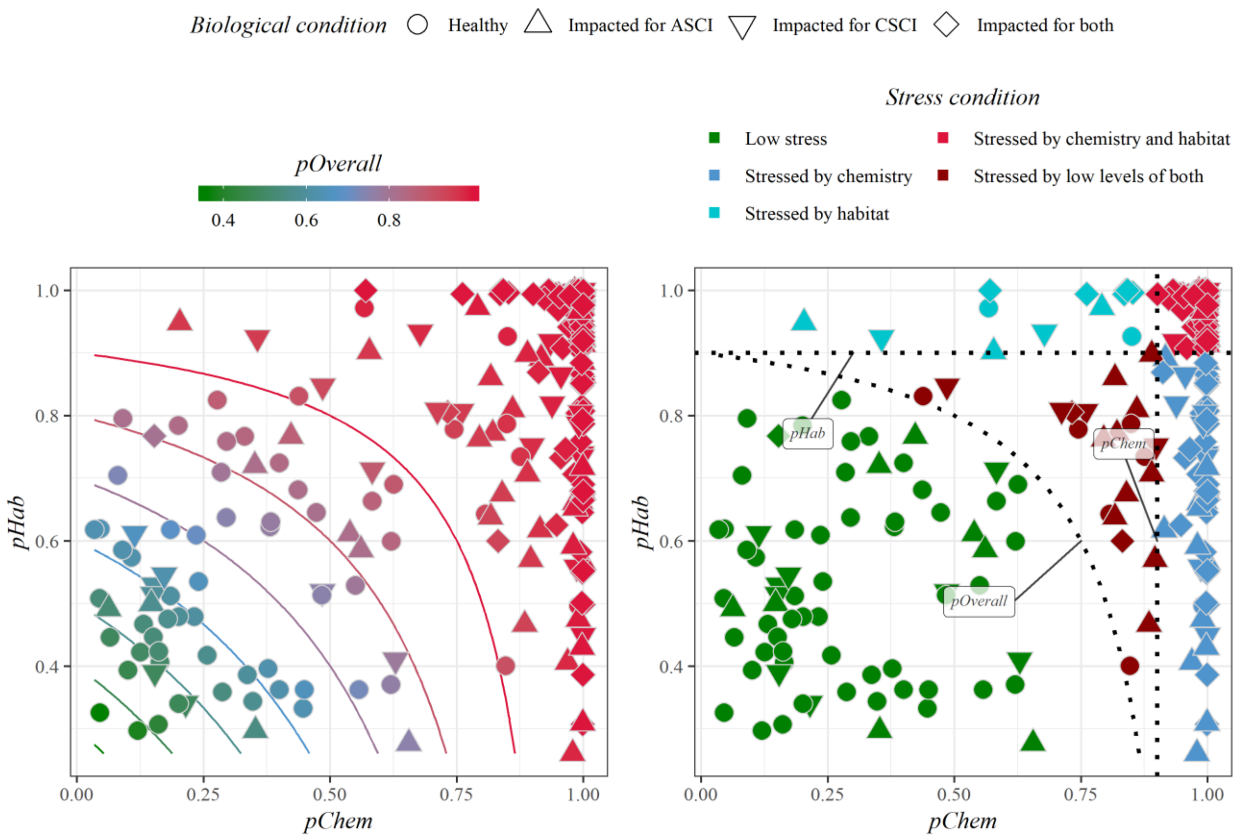

Figure 6. Relationship between stress models for water chemistry (pChem, eqn. (1)) and physical habitat (pHab, eqn. (2)). Stress models for water chemistry and physical habitat were created based on the likelihood of biological alteration for the observed stress measures. The overall stress measures (pOverall, eqn. (3)) is the product of both stress models shown in the left plot. Points represent estimated stress at a single site, with shapes showing the biological condition. The right plot shows the same points but colored by the stress condition categories that are defined by thresholds from the dotted lines.

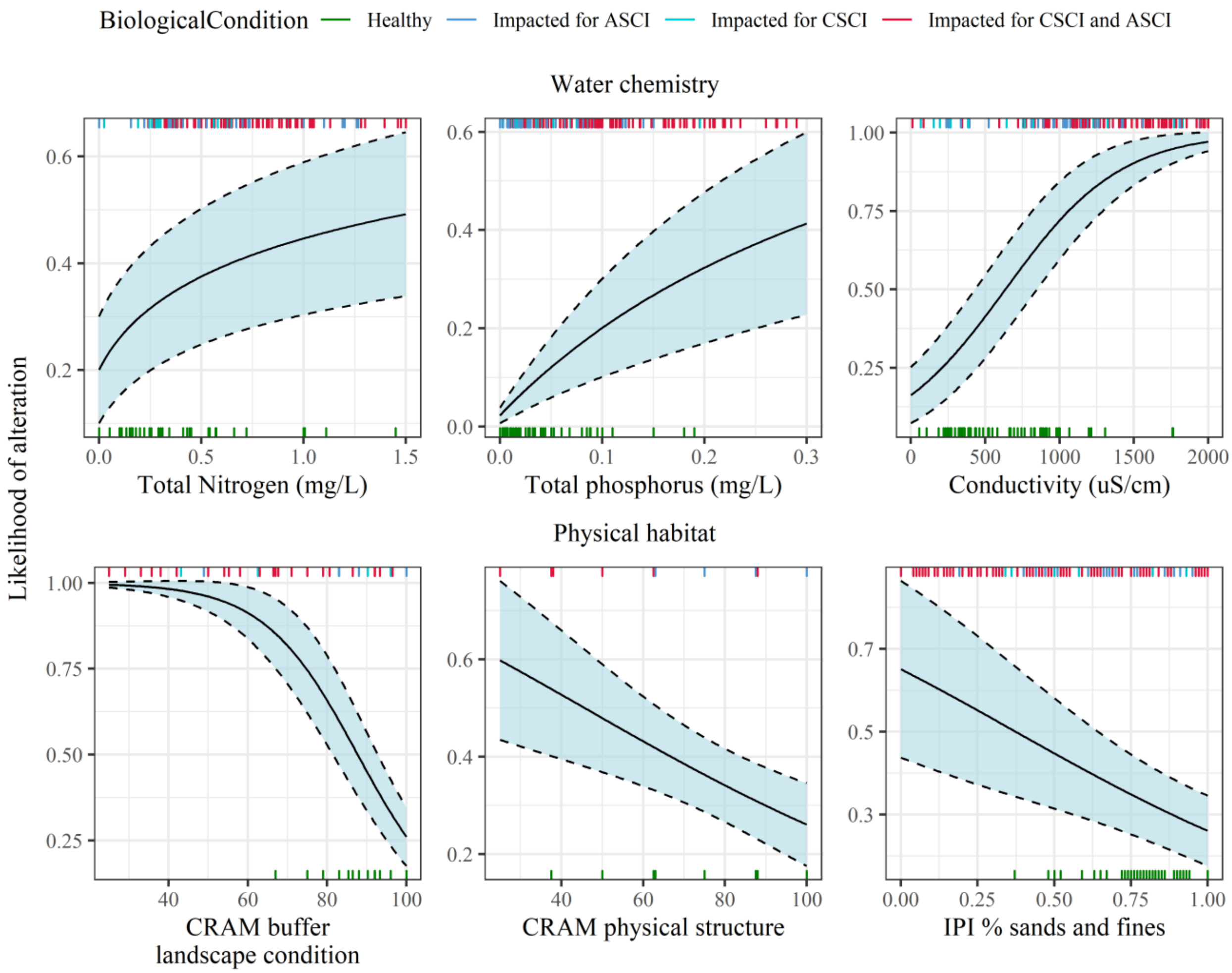

Figure 7. Modelled likelihood of biological alteration from water quality (top) and physical habitat stressors (bottom). Curves are the binomial likelihood (+/- standard error) of biological condition being altered (as measured by macroinvertebrate and algal indices) across the range of observed values for water quality and physical habitat stressors on the x-axes. The water chemistry and physical habitat stress plots are derived from equations (1) and (2). Other variables in each model not on the x-axis for each plot are held constant at values for low stress conditions. Biological condition for observations in each stressor model is shown as rug plots on the x-axes, with healthy sites on the bottom and impacted on the top.

Water chemistry and physical habitat predictors included in the empirical response models for *pChem* and *pHab* (equations (1), (2)) explained a substantial portion of variability among sites related to the occurrence of biological alteration (Table 3). The *pChem* model explained 64% of the variation among sites, whereas the *pHab* model explained 42%. All variables in the *pChem* model had VIF values less than 3 and were also included in the final set of predictors after model selection. All predictors in the *pChem* model were significantly and positively associated ($p < 0.05$) with the occurrence of biological alteration. For the *pHab* model, three predictors were removed that had VIF values greater than three (diversity of natural substrate, biological structure, and hydrology). Predictors included in the final *pHab* model after variable selection were buffer and landscape condition, physical structure, and percent sands and fines. All predictors were negatively associated with the likelihood of biological alteration, whereas buffer landscape condition had the only significant association.

Table 3. Summary of empirical stress models to quantify associations of water chemistry (pChem) and physical habitat (pHab) predictors with biological alteration. Generalized linear models were fit to predict the likelihood of both healthy benthic macroinvertebrate and algal communities at calibration sites (75% of n = 267 sites).

	pChem	pHab
Constant	1.68	11.02 ***
	(0.93)	(2.09)
log(TN)	1.12 *	
	(0.51)	
log(TP)	2.29 ***	
	(0.61)	
Conductivity	0.00 ***	
	(0.00)	
CRAM buffer landscape condition		-0.08 ***
		(0.02)
CRAM physical structure		-0.02
		(0.01)
IPI percent sands and fines		-1.67
		(1.00)
N	200	200
AIC	102.58	159.86
BIC	115.78	173.05
Pseudo R2	0.68	0.40

*** p < 0.001; ** p < 0.01; * p < 0.05.

Figure 7 demonstrates how the individual components for each stressor model were related to likelihood of alteration. These partial dependency plots were created by estimating the likelihood of alteration across a range of values for each predictor, while holding other predictors constant. For each plot, the variables in each model (equations (1), (2)) not on the x-axis were held at approximate values that were associated with low stress to better understand how biological alteration may be related to each predictor. For water chemistry stressors, all were positively associated with likelihood of alteration, particularly conductivity which had the steepest per-unit increase in likelihood. Associations of biological alteration with physical habitat predictors were also as expected, except that decreases in likelihood of biological alteration were observed with increases in the three predictors (all are associated with habitat integrity). The strongest relationship was observed with increases in CRAM buffer landscape condition, where likelihood of alteration decreased sharply with scores greater than 60.

Model sensitivity to biological decision points

Results in Figure 8 show changes in the categorical SQI results based on different decision points that defined biological condition. As a general trend, lowering the cutpoint for healthy/impacted to designate more sites as healthy (-6) resulted in an increase in the number of sites designated as "low stress" for the stress condition. For the overall SQI, lowering this cutpoint also increased the number of sites designated as "healthy and unstressed" or "impacted by unknown stress". Conversely, increasing the cutpoint for healthy/impacted to designate more sites as impacted (-6) caused in increase in the number of sites designated as "stressed by chemistry and habitat" for the stress condition and sites as "impacted and stressed" or "health and resilient" for the overall SQI.

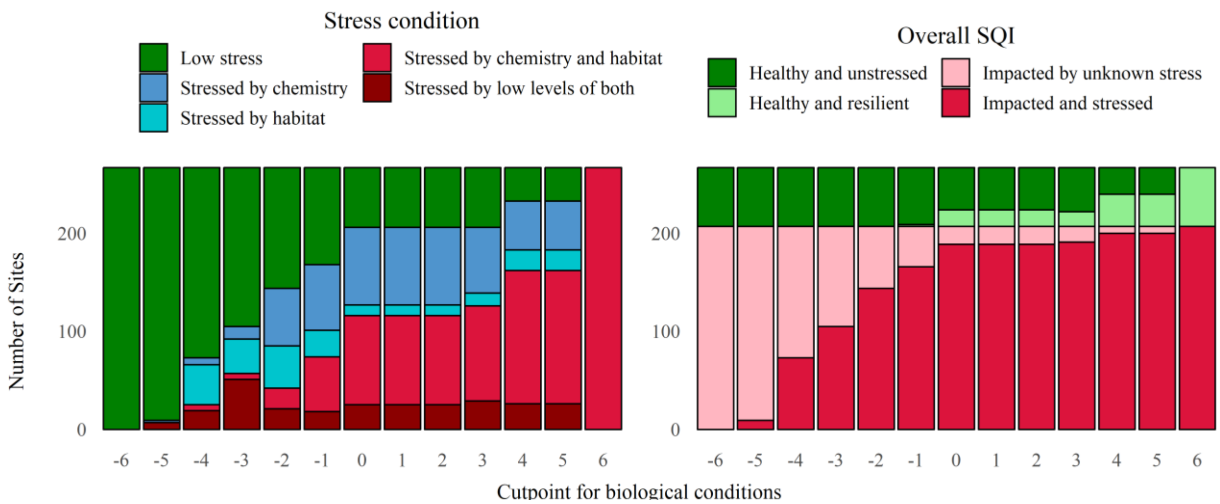

Figure 8. Changes in stress condition (left) and overall SQI categories (right) for different cut points that define healthy or impacted biology. Lower cutpoints mean more sites are designated as healthy, whereas higher cutpoints mean more sites are designated as impacted. The healthy/impacted categories are those modelled by equations (1), (2), and (3) that relate stress measures to biology. The cut point definitions are shown in Table 1.

Changing the threshold for the likelihood values that defined stressed biology also affected the categorical results (Figure 9). Higher thresholds shifted the number of sites to low stress conditions, whereas lower thresholds had the opposite effect of assigning more sites to high stress conditions. The number of sites that were stressed by low levels of both water chemistry and habitat conditions were relatively unchanged with different thresholds. The overall SQI categories were less affected by changing thresholds for the stress condition than for changing the cutpoint that defined healthy/impacted biology. However, higher thresholds shifted some sites from the impacted and stressed category to the impacted by unknown stress category and from the healthy and resilient category to the healthy and unstressed category.

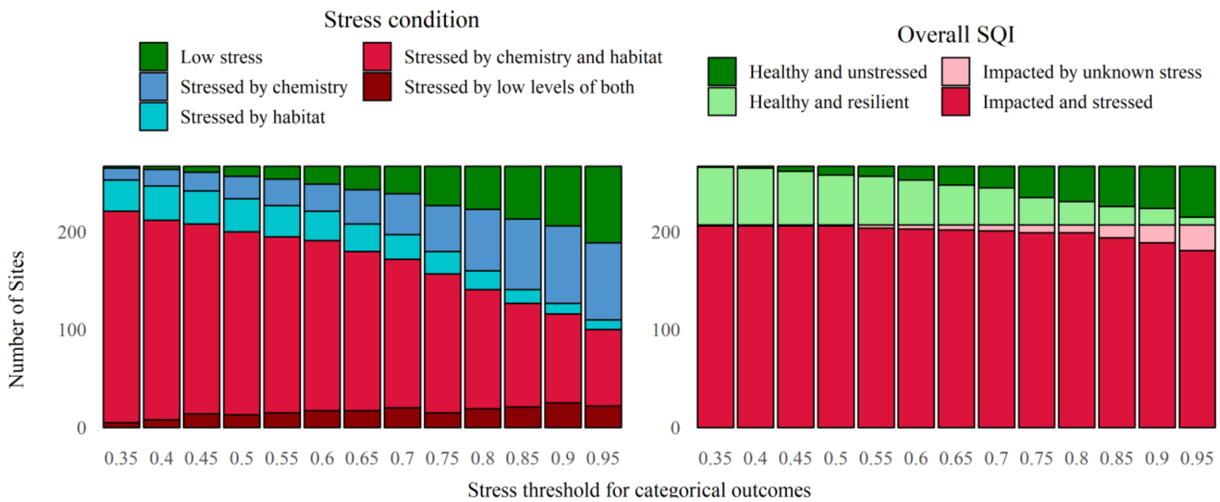

Figure 9. Changes in stress condition (left) and overall SQI categories (right) for different thresholds defining the stress categories. Lower thresholds mean more sites are designated as high stress, whereas higher thresholds mean more sites are designated as low stress. Sites are designated as low/high stress using the continuous likelihoods from the fitted models in equations (1), (2), and (3) that relate stress measures to healthy/impacted biology. The dotted lines in Figure 7 show stress thresholds set at 90%.

Case study results

San Diego Creek

San Diego Creek is a coastal stream in the County of Orange (33.689722N, -117.821853W) that drains the San Joaquin Hills and Loma Ridge into the Newport Bay estuary. The watershed is heavily urbanized and most of the creek has been engineered for flood control as a concrete-lined or reinforced channel with no natural riparian structure. The creek is designated for aquatic life (wildlife and warmwater habitat) and recreational (contact and non-contact) uses under the regional water quality control plan. Bioassessment results from the CSCI have shown that the structure and function of macroinvertebrate communities is very likely altered from reference conditions (Figure 10a).

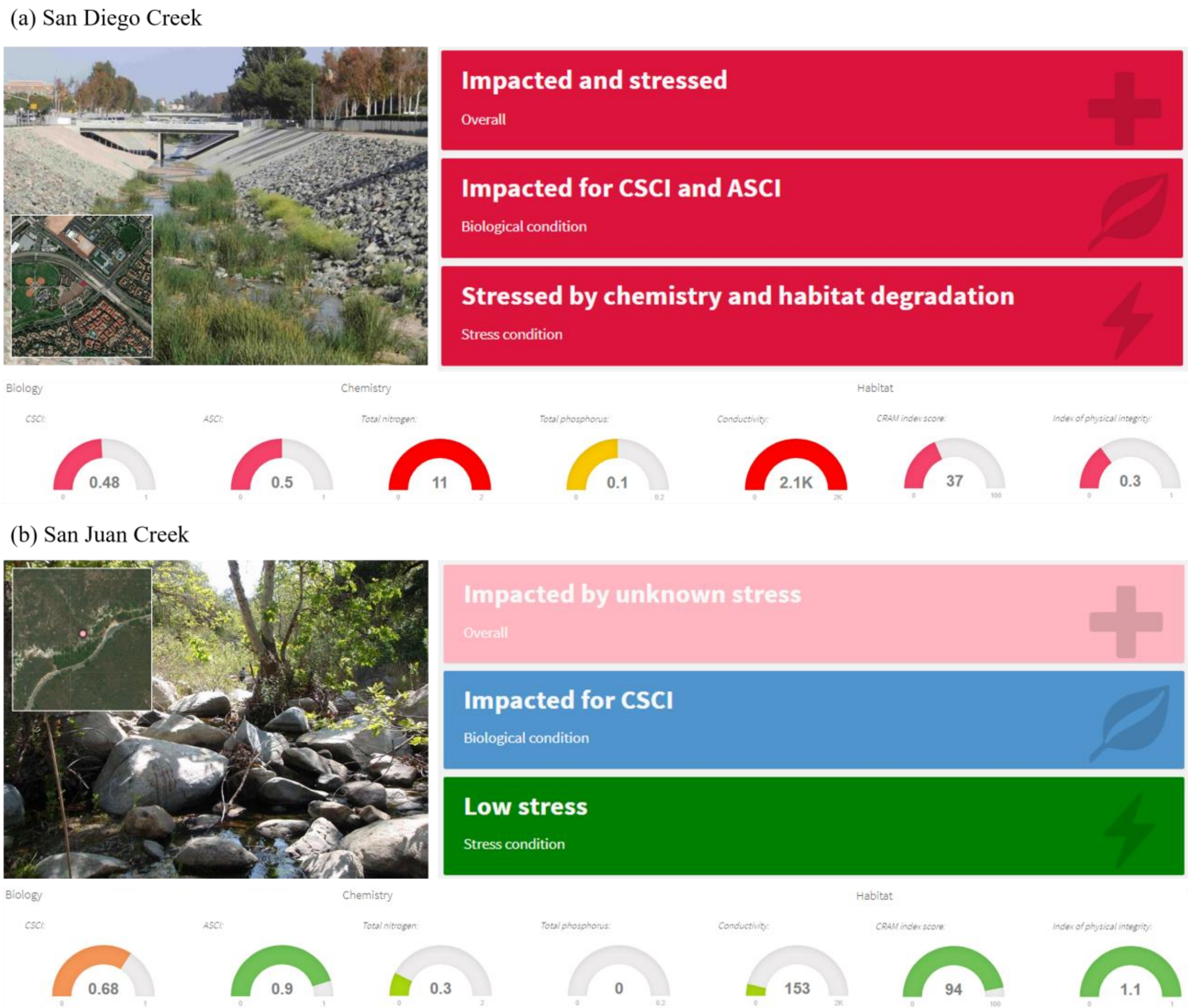

Figure 10. Results from the SQI for selected sites on (a) San Diego Creek (County of Orange, California, USA) and (b) San Juan Creek (County of Orange). Causal assessment analyses have been completed on San Diego Creek to identify stressors related to low CSCI scores. San Juan Creek is an example where biological impacts are observed, whereas chemistry and physical habitat stressors are low. Images are based on screenshots from the online application for exploring SQI results (see supplement, https://sccwrp.shinyapps.io/SQI_Shiny).

The dataset used to develop the SQI included five sites on San Diego Creek with one sample in 2010, three in 2011, and one in 2016. Biological condition at these sites was poor with ASCI scores ranging from 0.45 to 0.79 and CSCI scores ranging from 0.22 to 0.53. All sites were impacted for both CSCI and ASCI scores. The SQI stressor condition for all five sites indicated nearly a 100% likelihood of chemistry and physical habitat stressors impacting biology, with a 100% likelihood of overall stress based on the combined effects of both. Average total nitrogen, total phosphorus, and conductivity were 8.1 mg/L, 0.2 mg/L, and 2077 μS/cm, placing the creek in the 91st, 79th, and 75th percentiles for water chemistry, respectively, among all sites in the complete dataset. Similarly, CRAM and IPI scores averaged across sites were 46 and 0.52, placing the creek in the 24th and 23rd percentiles for the SMC region. The overall SQI category for all five sites was "impacted and stressed" (Figure 10a).

An independent causal assessment study was conducted in 2018 to determine the causes of biological impairment in San Diego Creek (Shibberu et al. 2018). A detailed description of causal assessment is beyond the scope of this paper, although in short, causal assessment is a formalized approach using multiple indicators to characterize stressors as likely, unlikely, or indeterminate causes for the biological condition observed in a system (Norton et al. 2014; Schiff et al. 2015). This differs from the SQI approach where the stressors are based on association alone. For San Diego Creek, the potential stressors that were evaluated included sediment accumulation, channel engineering, nutrients, temperature, conductivity, and pesticides. The causal assessment concluded that sediment accumulation and elevated water temperature resulting from channel alteration, combined with sediment-bound pesticides, were the most likely causes of low CSCI scores. Alternatively, nutrients, although elevated, were evaluated as not likely. The lack of a causal link between nutrients and biological condition may be related to the assessment's focus on CSCI scores as its biological endpoint and that sufficient algal data were unavailable at the time (ASCI scores were not evaluated). As such, the SQI results are supported by causal assessment, with the latter providing a more comprehensive evaluation of links between stressors and biological condition and insight into potential sources of the stressors.

San Juan Creek

San Juan Creek is located in the County of Riverside (33.606546N, -117.446041W) and drains into the Capistrano Bight, about 25 km south of Newport Bay. San Juan Creek originates in the Santa Ana mountains that are largely undeveloped, whereas lower portions of the creek are engineered for flood control in the urbanized areas of the watershed. The upper portion of San Juan Creek was described in a regional basin plan (San Diego Regional Water Quality Control Board) as not attaining aquatic life uses because CSCI scores were lower than the tenth percentile of scores observed at reference sites. However, both physical habitat and water chemistry parameters at the assessment site suggested conditions were adequate to support biotic integrity. Toxicity tests also showed 100% survival of *Ceriodaphnia dubia*, providing evidence that sediment contaminants (e.g., metals, pesticides) were unlikely stressors impacting biology at the site.

The SQI results for the sampling station in the upper San Juan Creek confirmed the above results by categorizing the site as "impacted by unknown stress" (Figure 10b). The CSCI score at the site is 0.68, whereas the ASCI score is close to reference conditions at 0.94; the biological condition category for the SQI indicates the site is impacted for the CSCI only. The likelihood of biological alteration was estimated as 15% from chemistry stress and 51% from physical habitat stress, with a combined likelihood of 59% from overall stress. Total nitrogen, total phosphorus, and conductivity were 0.3 mg/L, 0 mg/L, and 153 μS/cm, placing the site in the 21st, 7th, and 2nd percentiles for water chemistry, respectively, among all sites. Similarly, CRAM and IPI scores were 94 and 1.06, placing the creek in the 98th and 85th percentiles for the SMC region. As such, initial results suggest that neither chemistry nor physical stressors are impacting biological condition. Chosen management actions at this site are dependent on regional priorities and applicable regulatory requirements.

DISCUSSION

The Stream Quality Index offers a solution for watershed managers seeking to synthesize large amounts of physical, chemical, and biological data about stream health. Using the SQI, users can both recognize large-scale patterns in data from multiple indicators, and improve how the data are communicated to high-level, non-technical environmental managers. This need is particularly pressing in regions like southern California, where large-scale landscape alteration and competing demands for water usage require managers to prioritize limited resources and management actions. As shown by the application of the SQI to stream data from southern California, this tool can be used to prioritize sites for management activities on a large scale. Conversely, the SQI can be used as a valuable communication tool to highlight areas where biological objectives are not being met, perhaps motivating additional investigations to identify specific stressors in a more rigorous framework (e.g., San Diego Creek case study).

While the simplest way to synthesize indicators would be to treat them equivalently and simply "average" the results, this approach would mask the types of information provided by each, and ultimately could not effectively characterize situations where these indicators disagreed – a common situation in the SMC data set. Dobbie and Clifford (2014) evaluated sources of uncertainty for an integrative index of estuarine health that was based on averaging separate water quality components across different spatial units. By their own admission, averaging indicators raised concerns about the consistency and validity of interpretation and their results showed that the composite index was indeed sensitive to the parameters for averaging. Accordingly, To properly capture relationships among indicators of stream quality in a way that is consistent with conceptual modeling of a healthy stream ecosystem, it was crucial to develop an index that accurately reflects biology's role as a direct measure of condition, and that reflects physical and chemical indicators as measures of stress. In other words, a finding of good water chemistry should not obscure or distort an indication of poor biology, and vice versa.

As a categorical index, the SQI provides a readily interpretable description of stream conditions that is easily accessible through a web-based application. The four condition categories defined by the index (i.e., healthy and unstressed, healthy and resilient, impacted and stressed, impacted by unknown stress) can be understood by a general audience that may not need the underlying data and tools used to analyze them. In contrast, numeric indices require a benchmark or other appropriate context to interpret scores; without this information, it can be difficult to identify which values of a numeric index correspond to healthy conditions requiring protection, and which values correspond to impacted conditions requiring intervention. Defining the condition categories from empirical models that are ultimately linked to continuous data provided a quantitative link between the two.

The SQI also addresses the challenge of synthesizing large amounts of information about stream condition without losing the individual components, which are readily available to the user for more in-depth exploration because the index is hierarchical. This provides a critical service by allowing users to identify likely reasons behind the categorical classification for a given site. In other words, users can determine which biological indicators account for a stream's health rating, along with which stressors may or not be associated with biological condition. Users also can identify presence or absence of physical and/or chemical stressors included in the empirical model, and which components in equations (1) and (2) may be linked to their respective stressor categories. Further, physical habitat measures (i.e., CRAM and IPI) include component metrics that can serve as additional diagnostic information to describe physical conditions (e.g., percent sands and fines, shading, diversity of natural substrates, etc.). An evaluation of component metrics for sites that are stressed by physical habitat may reveal which stream characteristics could be prioritized to improve condition (e.g., reduce bank erosion or increase riparian cover).

Tools that are similar to SQI have been developed, although key differences exist. The Canadian Water Quality Index (CWQI, CCME (Canadian Council of Ministers of the Environment) (2001), Hurley et al. (2012)) evaluates the scope, frequency, and amplitude of water quality objective exceedances for numerous parameters, resulting in a numeric value that ranges from 0 (poor) to 100 (excellent). This approach is appropriate for assessing compliance with regulatory criteria at sites where monitoring covers many parameters and occurs at regular intervals (i.e., at selected sites of interest, such as below discharge points or at mass-emission stations). In contrast, the SQI is better suited for ambient monitoring programs (e.g., Mazor (2015); USEPA (U.S. Environmental Protection Agency) (2016)) that typically sample many sites with little or no replication and that focus on just a few indicators broadly indicative of water chemistry conditions rather than a large suite of potential stressors. Our approach is also applicable to indicators where thresholds are unavailable (e.g., CRAM or IPI), but where the relevance for measuring aquatic life support is maintained even when it has less bearing on regulatory compliance than with other approaches, such as the CWQI. Finally, the SQI approach can be directly interpreted without familiarity of established benchmarks because the empirical stress models in the SQI are expressed as probabilities of degrading biological condition, rather than discrete thresholds that may not have context.

Our theoretical framework for the SQI is not without drawbacks. The index as designed cannot accommodate additional or fewer indicators of stream condition/stress - a contrast to the CWQI that can include any number of available parameters. Missing data (e.g., lost samples or incomplete coverage of required data at a site) prevent calculation of the complete SQI, and the index cannot be estimated without recalibration to include or exclude individual components. However, partial output for the SQI can be obtained if, for example, only stressor data are available. The overall SQI category cannot be assigned to a site for incomplete data, but the sub-categories (e.g., biological condition category or stressor condition category) can still be obtained where the data are available.

At the same time, the initial SQI described herein was purposefully restricted to a limited number of parameters to focus on developing the foundation of the index, as we were aware that a broader scope could preclude many sites from analysis. For example, CSCI and ASCI scores for the biological components of the SQI are available at over 1,000 sites in southern California, but combining these data with the required chemical and physical stressor data reduced the total number of sites where all components were available to 267 sites. An additional concern is our choice of predictors that were purposefully limited to the most relevant and ubiquitous data for describing eutrophication (water quality) and instream/riparian condition (physical habitat) in the study region. We realize that these variables are proxies and may also be correlated with other variables (e.g., stream temperature). Thus, causation can only be partially inferred with our models and more rigorous follow-up work would be needed to identify specific stressors. Similarly, recalibration of the model and choosing appropriate thresholds for defining categorical output would be required if the framework were applied in a different setting or context (e.g., different regions or stressor gradients). This may also apply to the current dataset as new observations become available to best describe regional conditions.

The SQI web application

A web application was developed to make the SQI - and all of the foundational data for the overall SQI assessment - accessible to a broad user base, that in turn can readily share findings with high-level, non-technical managers and other stakeholders (https://sccwrp.shinyapps.io/sqi_shiny). The web interface uses an open source software program developed in R (Chang et al. 2018; RDCT (R Development Core Team) 2018) to automate batch calculation of the SQI at large numbers of sites (Beck and Mazor 2018). This allows the index and web application to be easily updated as new data become available for sites already in the database.

The web app's visualization features also support exploration of the data at both regional and site scales, encouraging users to explore results in different spatial contexts. Scores for each index component are provided alongside the option to view the underlying data that were used for the empirical stress models and categorical outcomes. A map allows for rapid comparison of sites of interest to the region as a whole, as well as county- or watershed-level summaries. The case study examples for San Diego and San Juan Creeks complemented site-specific information about each site to demonstrate how the SQI and its web application can support management decisions. With this information, managers can prioritize follow-up actions to identify causes of biological impacts (e.g., wildfire, bank erosion, or other sources) or pursue other appropriate management actions (e.g., formal causal analysis or site restoration). As such, the web application provides a screening tool to rapidly assess condition and identify potential stressors that may be impacting condition – insights that would be more difficult to identify via traditional research products (e.g., tabular data).

Conclusions

An integrated stream health index that synthesizes physical, chemical and biological indicators could be a powerful tool to support watershed management. The SQI accurately captures our understanding of the roles that physical, chemical and biological indicators play in describing stream health. Furthermore, the SQI not only combines the data into a single, managerially relevant categorical classification, but the tool also preserves the data underlying the integrated assessment, enabling managers to readily access this information as they work to better understand the reasons behind the overall assessment.

The SQI is a viable approach for managers that need to synthesize large amounts of data, assign priorities based on this synthesis, and communicate these decisions to a broad range of high-level managers and other stakeholders who may lack familiarity with bioassessment and/or watershed science. In particular, the SQI could be used to convey critical insights for routine watershed assessments, permit reporting, and environmental report cards. Although the SQI is calibrated and validated specifically for southern California, USA, the approach could be applied anywhere with sufficient data. Many national and international monitoring programs that have collected data for several years could easily apply the SQI framework with alternative biological endpoints or stressor data.

SUPPLEMENT

An interactive website is available for viewing results of the SQI: https://sccwrp.shinyapps.io/SQI_Shiny (Beck et al. 2019). An R package is also available for calculating SQI scores: https://github.com/SCCWRP/SQI (Beck and Mazor 2018).

ACKNOWLEDGMENTS

We thank the Stormwater Monitoring Coalition and Surface Water Ambient Monitoring Program of the California State Water Board for data collection. We thank the Stormwater Monitoring Coalition executive committee and science advisory group for feedback during the development of the Stream Quality Index. Members of the science advisory panel included Beverley Anderson, Ali Dunn, Chad Loflen, Phil Markle, Katherine Pease, Grant Sharp, Hoan Tang, and Joshua Westfall. We thank David Gillett, Chad Loflen, Grant Sharp, and Joshua Westfall for help with the case studies. We thank Scott Martindale for providing editorial comments on an earlier draft. We thank Nabiul Afrooz for initial contributions on the conceptual framework for the index. Site photos for the case studies courtesy of David Gillett (San Diego Creek) and Chad Loflen (San Juan Creek).

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