Quantifying biological constraints on stream integrity for classification and management priorization

Marcus W. Beck (marcusb@sccwpr.org), Raphael D. Mazor (raphaelm@sccwrp.org), Scott Johnson (scott@aquaticbioassay.com), Phil Markle (phil@lacsd.org), Peter D. Ode (peter.ode@wildlife.ca.gov), Ryan Hill (hill.ryan@epa.gov), Eric D. Stein (erics@sccwrp.org)

Introduction

- Degraded biological condition in streams can occur from individual or multiple stressors acting at different scales (Novotny et al. 2005; Townsend, Uhlmann, and Matthaei 2008; Leps et al. 2015). Identifying and mitigating causes of poor condition requires an understanding of how stressors propogate across space and time. Incomplete knowledge on drivers of change or high level of uncertainty in how biology is linked to drivers can lead to ineffective management actions. Varying expenses and assurance of outcomes (e.g., varying costs and challenges of urban stream restoration (Kenney et al. 2012; Shoredits and Clayton 2013))
- Stream restoration relies extensively on identification and prioritization of sites where activities are expected to have desired outcomes. This requires an understanding of how stressors affect biological integrity to place bounds on reasonable expectations for what is likely to be a possible outcome of a management action. This requires identifying biological constraints or limits on the potential range of biological conditions. Identifying an appropriate context for observed conditions can be used to prioritize. Context can be defined by models, expert knowledge, and/or defined value sets.
- We don't have good constraint tools to develop a context of expectation of what's possible at a site. This can help prioritize locations where management efforts will or will not have the intended outcomes. Biological filters act at different scales (Poff 1997) and we can use this information to describe an expectation for prioritization that is scale-specific. Landscape-level constraints are particularly relevant for macroinvertebrate communities in streams (Sponseller, Benfield, and Valett 2001)
- The goal of this study is to demonstrate application of a landscape model to classify and prioritize stream monitoring sites using estimated constraints on biological integrity. The model provides an estimate of context for biological condition that provides an expectation of what is likely to be achieved at a given site relative to large-scale drivers of stream health. The model was developed and applied to all stream reaches in California. A case study is used to demonstrate how the model can be used to classify and prioritize using guidance from a regional stakeholder group. Active stakeholder involvement was critical in applying the landscape models to define a framework for decision-making because priorities varied with management objectives.

Methods

Study area and data sources

- Brief description of CA, stream types and designated uses, PSA regions, management interests (e.g., southern vs. northern CA)
- Streamcat database used to quantify watershed land use at all sites (Hill et al. 2016)
- Streamcat data linked to National Hydrography Dataset Plus (NHD) (USGS (US Geological Survey) 2014), reach as individual unit for model output

The California Stream Condition Index (CSCI) (Ode et al. 2016; Mazor et al. 2016) was used as a measure of biological condition to assess site performance relative to reach classification. Benthic macroinvertebrate data used to calculate CSCI scores were collected at nearly 4800 sites between 2000 and 2014. Field data were collected during baseflow conditions typically between May and July following methods in Ode (2007). The CSCI is a predictive index of stream health that compares the observed taxa and metrics at a site to those expected under reference conditions. Expected conditions at a site are based on models that estimate the likely macroinvertebrate community in relation to factors that naturally influence biology, e.g., watershed size, elevation, climate, etc. The CSCI score at a site is based on an observed-to-expected ratio of taxa and a predictive multimetric index (pMMI) composed of six individual metrics that describe the structure and function of the macroinvertebrate community. The index score at a site can vary from 0 to 1.4, with higher values indicating an observed community with less deviation from reference conditions. Because the index was developed to minimize the influence of natural gradients, the index scores have consistent meaning across the state (Reynoldson et al. 1997). A threshold score based on a selected lower percentile of scores (e.g., 10%) at all reference sites is used to define nominally low and high scoring sites.

Building and validating landscape models

A prediction model of the CSCI was developed to estimate likely ranges of scores associated with land use gradients. Land use as urban and agricultural was quantified for the catchment of each stream reach in California using the StreamCat database (Hill et al. 2016). CSCI scores were modelled using only the the estimates of urban and agricultural land use as the developed portion of the landscape within each stream reach. The model was incomplete by design to describe scores only in relation to large-scale constraints on biological condition that are not easily controlled by management actions or where costs to mitigate are likely to be excessive. The remainder of the variation in scores not related to landscape constraints could be attributed to additional, unmeasured environmental variables that influence stream biointegrity. Deviation of observed scores from the model predictions were considered diagnostic of variation not related to landscape effects.

Models were developed using quantile regression forests to estimate ranges of likely CSCI scores in different landscapes (N. Meinshausen 2006; Nicolai Meinshausen 2017). Quantile models evaluate the conditional response across the range of values that are expected, such as the lower and upper percentiles of the distribution, as compared to only the mean response with conventional models (Cade and Noon 2003). This allows use of model predictions to describe where bioassessment targets are unlikely to be met or where streams are unlikely to be impacted by placing bounds on the range of expectations relative to landscape constraints. Random forest models also provide robust predictions by evaluating different subsets of observations from random splits of the predictor variables. The final predictions are the averaged response across several models. These models have been used extensively in bioassessment applications (Carlisle, Falcone, and Meador 2009; Chen et al. 2014; Mazor et al. 2016) and can produce unbiased estimates that are relatively invariant to noisy relationships or non-normal distributions (Breiman 2001; Hastie, Tibshirani, and Friedman 2009). Quantile regression forests were used to predict CSCI scores in each stream reach from the 5^{th} to the 95^{th} percentile of expectations at five percent intervals (i.e., 5^{th}, 10^{th}, etc.).

Landscape eestimates for the catchments of all NHD stream reaches in California were separated into calibration and validation data.

Classifying streams and prioritizing sites

A framework for identifying site priorities for categories of management actions was developed using a three-step process. First, estimates of the range of expected CSCI scores at each stream reach in relation to land use were used to define reach classifications. Second, the relationship between observed CSCI scores and the reach classifications were then used to assign a relative performance value for each monitoring site. Third, site performance categories in relation to reach classification and bioassessment targets were used to define management priorities. This framework was developed through close interaction with a regional stakeholder group with broad representation of interests in stream management. This process was used to demonstrate how the landscape model can be used as a management tool given that priorities will vary by interests and location. As such, the results are provided as a guide to facilitate decision-making rather than a prescription of targeted actions to manage stream health.

Stream reach and bioassessment data from the San Gabriel River (SGR) Watershed in southern California were used to develop reach classifications, site performance categories, and management priorities from the landscape models. A strong land use gradient occurs in the SGR watershed. Headwaters begin in the San Gabriel mountains where the land is primarily undeveloped or protected for reacreational use, whereas the lower watershed is in a heavily urbanized region of Los Angeles County. The San Gabriel river is dammed at four locations for flood control in the upper watershed and is hydrologically connected to the Los Angeles river to the west through the Whittier Reservoir in the lower watershed. Spreading grounds are present in the middle of the watershed for groundwater recharge during high flow. Nearly all of the stream reaches in the lower half of the watershed are channelized with concrete or other reinforcements.

Figure SGR watershed

The SGR watershed contains a diverse group of stakeholders from local municipalities, water districts, water quality regulatory agencies, consulting groups, and non-government organizations. Collectively, the San Gabriel River Regional Monitoring Program (SGRRMP) includes stakeholders from these groups that cooperatively work to increase awareness of issues in the SGR watershed and work to improve coordination of compliance and ambient monitoring efforts. The stakeholder workgroup included individuals from the SGRRMP with interests in water supply, improvements to water quality, habitat protection or creation, and storm water permitting. Individuals were selected for partipation to include a variety of mangement interests and based on willingness to adopt tools developed from the landscape models. The stakeholder workgroup met monthly over a six-month period to discuss model applications and to refine the interpretation of results. Stakeholder involement was critical for developing an assessment framework that met the needs of all engaged parties and ensured that final products were more likely to be incorporated into formal processes of decision-making.

- Methods for estimating stream class - possibly/likely constrained, possibly/likely unconstrained, certainty and CSCI threshold, some sites were unclassified

Figure classification and performance

- Methods for estimating site performance - over, expected, underperforming, discussion of site types
- Sensitivity analysis - how do classes, performance categories change with thresholds and certainty
- Prioritization of types - stakeholder involvement

Results

State-wide patterns

- Where does the model perform well, how does performance vary with validation and calibration datasets.
- What is the consistency of patterns? For example, percent stream miles as xyz by PSA.

Figure Statewide map.

Case study

- San Gabriel River Regional Monitoring Program
- Extent, classification, prioritization - probabilistic assessment to make broader conclusions.

- Relationships with environmental variables for constrained/unconstrained locations. Maybe apply to hardened/non-hardened reaches in constrained locations.
- What to do with unclassified streams - typical urban, typical ag.

Tables Priority by type, by perspective

Discussion

- What do priorities really mean? Depends on your interests, needs, values, etc.
- Link with engineered channels study.
- Values of stakeholder interactions.

Supplement

Online application.

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