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Comparing assembly processes for multimetric indices of biotic integrity

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ABSTRACT

Anthropogenic alterations to global ecosystems necessitate management action to conserve or restore biodiversity and ecosystem services. A major advancement in ecosystem management was the development of multimetric indices of biotic integrity (MMIBI) used to guide development of, and measure progress towards, restoration goals. Despite considerable refinement of MMIBI applications over the past three decades, a central challenge remains concerning the method of selecting ecological indicators for inclusion in MMIBI. We quantitatively compared MMIBI metric assembly processes across four sub-regions for fish assemblages in western Tennessee, USA to assess relative performance of three metric selection approaches. Metric selection methods we assessed included "filter gradient" using a multi-step approach to filter candidate metrics down to only the most reproducible and responsive, "indirect gradient" using a correlative unconstrained ordination approach, and "direct gradient" involving an automated constrained ordination approach. For each method, we calculated MMIBI using the selected metrics and compared their precision (i.e., stability across multiple samples), responsiveness (i.e., discrimination between most- and least-altered sites), and sensitivity (i.e., ability to detect landscape alterations). We found metric selection using the filter gradient approach produced MMIBI that were most responsive across all four sub-regions, while the indirect gradient approach produced the most sensitive and precise MMIBI for three of four sub-regions. The direct gradient metric selection approach produced the most sensitive MMIBI only for a single sub-region with a relatively short gradient in landscape alterations. These results reveal a tradeoff between filter and indirect gradient selection methods in which filter gradient metric selection provides high MMIBI responsiveness, but at the cost of increased number of steps and reduced precision and sensitivity. The "middle of the road", indirect gradient metric selection approach produced precise and sensitive MMIBI, but at the cost of reduced responsiveness. These findings highlight the necessity to pair well-developed ecosystem management goals with MMIBI application, and provide a road map for the most appropriate assembly process for managers developing MMIBI. For example, identification of least- and most-altered sites might best be accomplished with MMIBI developed using the filter gradient approach, but assessing the factors contributing to alteration and precisely measuring progress towards restoration endpoints might best be accomplished with MMIBI developed using the indirect gradient approach. Restoration and management actions guided by MMIBI will become increasingly prevalent with increased future alteration to global ecosystems, and this work provides important insight into how technological and quantitative advances will improve application of ecological indicators.

1. Introduction

Humans transform landscapes on a global scale in response to economic opportunities and societal needs (Lambin et al., 2001). Abundant evidence suggests anthropogenic landscape alterations involving land cover change stress natural ecosystems and diminish the value of natural resources (Costanza et al., 1997; Hughes et al., 2015; Pinto et al., 2009). Although the geographic location of ecosystems and their position along gradients of climate, soil, landform, and land use ultimately determine the magnitude of stress caused by landscape alterations (Abell et al., 2000), aquatic ecosystems and their biota are disproportionately affected relative to terrestrial ecosystems (Dudgeon et al., 2006). Aquatic ecosystems are influenced by terrestrial landscape alterations through hydrologic connectivity, or the water-mediated movement of matter, energy, and organisms across terrestrial-aquatic ecosystem boundaries (Burcher et al., 2007; Pringle, 2003).

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Understanding consequences of land cover alterations, as they relate to aquatic resource sustainability and conservation, requires tracking ecological changes across space and time; however, determining the most appropriate, efficient, and comprehensive manner for tracking change is a difficult process (Dale and Beyeler, 2001; Niemeijer and de Groot, 2008).

Ecological (or biological) indicators representing the integrity of ecosystems have evolved as broadly applied tools for rapid assessment of aquatic systems. Ecological indicators are widely used as a pragmatic approach to understand how ecosystems respond to stressors by providing measurable, stress-sensitive, and predictable metrics that inform the condition of an ecosystem (Cairns et al., 1993; Dale and Beyeler, 2001; Niemi and McDonald, 2004). Common ecological indicators assess the structure, function, and composition of communities and include metrics such as population size and biodiversity measured at taxonomic and functional levels (Hoeinghaus et al., 2007; Landres et al., 1988). The index of biotic integrity (IBI) developed by Karr (1981) measures broad-scale ecosystem integrity based on census data from local fish communities. The conceptual basis for the IBI is that local fish assemblage structure is an artifact of the local habitat plus broader scale anthropogenic alterations present within the watershed (Angermeier and Winston, 1998; Cunico et al., 2012; Esselman and Allan, 2010). Within the IBI framework, delineation of biotic integrity is achieved when several biological metrics are compiled to create a range of values a stream might exhibit, with lower values indicating high stress, and the distribution of IBI values across a region acting to inform management targets for mitigation of stressors (Fausch et al., 1984). Matching IBI scores from a focal site with a reference site that represents a least-altered condition can guide management of landscapes and provide a measure of progress towards restoration goals (Hughes, 1995). Since its inception, the IBI framework has been applied worldwide to a variety of ecosystems and organisms (Chen et al., 2017; Esselman et al., 2013; Karr and Chu, 1998; Ruaro and Gubiani, 2013). However, advanced application of the IBI framework has increased in complexity along multiple fronts, including: (1) identification, measurement, and scaling of large numbers of metrics (Dale and Beyeler, 2001), (2) simultaneous screening of multiple metrics so that only those useful for measuring integrity are included in assessments (Niemeijer and de Groot, 2008), and (3) coupling landscape alterations with biological metrics (Allan et al., 1997). Because of these issues, modern derivations of the IBI include application of multimetric indices of biotic integrity (MMIBI) that include trait-based classifications of fishes and either reference sites or some statistical derivation from non-altered biotic condition (Ruaro and Gubiani, 2013; Stoddard et al., 2006; Yates and Bailey, 2010). However, the manner in which metrics are selected to be included within an MMIBI requires additional research.

A central challenge facing the development and application of MMIBI is determining the most appropriate method for selecting metrics to be included in composite calculations. While many previous criticisms of MMIBI (e.g., ambiguous index score relevance, eclipsing of low metric values by high; Suter, 1993) have already been addressed (e.g., dissection of score values using reference sites and integrity gradients; Simon, 1998), the challenge of assembling only the most useful metrics within an MMIBI remains. In some cases, as many as 237 candidate metrics might exist (e.g., Whittier et al., 2007a) and subjectivity (e.g., professional judgement, arbitrary thresholds) can be introduced through the methodology used to select metrics from larger pools (Miranda et al., 2012). One approach to selecting the most suitable metrics from a candidate pool is a series of steps designed to filter candidate metrics according to gradients in metric range, variation along natural gradients, reproducibility, responsiveness, and redundancy (hereafter: "filter gradient"). This approach has been employed for fish communities (Carvalho et al., 2017; Esselman et al., 2013; Whittier et al., 2007a) and aquatic invertebrates (Chen et al., 2014; Stoddard et al., 2008) despite criticisms concerning the large number of steps and possibility for introducing subjective selection thresholds into the process (Miranda et al., 2012). Alternative methodologies include multivariate approaches to metric selection, such as unconstrained ordinations that produce multivariate arrangements of sites based on Euclidean distances calculated from landscape alterations, and then iteratively solve for similar arrangements of sites based on distances calculated from candidate ecological metrics (hereafter: "indirect gradient"; Clarke and Ainsworth, 1993). This approach was recently applied to select the subset of candidate metrics that best explained spatial variation in fish communities caused by reservoir release operations (Ivasauskas and Bettoli, 2014) and represents a multivariate extension of the correlative approach used in filter gradient selection. Finally, a direct gradient multivariate analysis in which variation in candidate metrics is constrained by environmental variables allows for a purely data-driven approach to metric selection (hereafter: "direct gradient"; Legendre and Anderson, 1999). This method was recently applied to fish communities in oxbow lakes to determine the subset of candidate metrics that best explained variation in environmental characteristics of lakes (Miranda et al., 2012). Although multivariate metric screening methods have benefits in terms of reduced number of steps and judgment effort compared to filter gradient screening, no quantitative comparison exists for determining which MMIBI assembly procedure produces the most precise, responsive, or sensitive MMIBI.

In this study we quantitatively compare MMIBI assembly methods and determine if trade-offs exist across methodologies or if a single method is superior in terms of MMIBI precision, responsiveness, and sensitivity (Fig. 1). The first objective was to compile landscape alterations and candidate MMIBI metrics using fish assemblage data, remotely-sensed anthropogenic alterations, natural land cover, and abiotic stream variables for four sub-regions in west Tennessee, USA. Our second objective was to use three commonly applied metric selection processes across all four sub-regions. Our third objective was to quantitatively compare metric selection processes to evaluate precision, responsiveness, and sensitivity of MMIBI produced for each sub-region. We conducted our study in a global fish biodiversity hotspot within the southeastern USA (Abell et al., 2008) where large numbers of endemic species present unique challenges in terms of the number of ecological indicator metrics needed to measure biotic integrity.

2. Methods

2.1. Study area

We studied stream fish communities and landscape alterations in a western portion of Tennessee, USA. Normal annual air temperatures range from 10 to 22 °C across this region and it receives an average of 136.9 cm of rain per year (NOAA, 2017). Streams in this area are distributed among portions of the Mississippi and Tennessee River catchments and fall within three Environmental Protection Agency (USEPA) Level 3 Ecoregions (Omernik, 1995, 1987), including Mississippi Valley Loess, Southeastern Plains, and Interior Plateau (Fig. 2). While divides between ecoregions can present gradients of conditions rather than distinct lines, ecoregions still provide clear boundaries for management units and provided the template for partitioning sub-regions for this assessment (Omernik, 1995). Because of known biogeographical breaks in fish distributions between the Mississippi and Tennessee catchments (i.e., 24 endemic to the Mississippi, 91 endemic to the Tennessee; Etnier and Starnes, 1993), we split the Southeastern Plains ecoregion based on the catchment divide to create the Southeastern Plains Mississippi tributaries (SEPMS) and Southeastern Plains Tennessee tributaries (SEPTN) sub-regions. This split resulted in four sub-regions total, including SEPMS, SEPTN, Mississippi Valley Loess (MSV), and Interior Plateau (INP). Within each sub-region, we used a geographic information system (GIS; ESRI 2015) and data from the National Hydrography Dataset (USEPA and USGS, 2012) to assign abiotic and biotic values for MMIBI evaluation. Splitting sub-regions based on drainage centroids in