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Incorporating species losses and gains into a fish-based index for stream bioassessment increases the detection of anthropogenic disturbances

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ABSTRACT

The taxonomic completeness index (ratio of observed to expected species; O/E) is widely used in stream bioassessment programs to infer ecological impairment. However, its sensitivity to detecting anthropogenic disturbances may be reduced by (1) the modelling procedure used to determine the expected species at a site (2) the inability of the index to account for assemblage shifts through species gains as well as losses; and (3) the frequent use of a threshold that only allows assessment of the absence of prevalent species. We used a version of the BC biotic index (an adaptation of Bray-Curtis distance) that incorporated alien and translocated species into the observed component, and generated expected native species probabilities using single species ensemble models (‘BC_A’). Sensitivity analysis, bivariate correlations and multiple linear regression analyses were used to test whether BC_A better detected anthropogenic disturbances than the standard BC (i.e. without alien and translocated species) and O/E_{50} derived from the same models. We also tested three additional fish biotic indices currently used in the Ecosystem Health Monitoring Program in Southeast Queensland, Australia. Of the indices tested, BC_A explained the greatest amount of variance in anthropogenic disturbance variables, followed by BC and the proportional sample abundance of alien species. The BC_A index was 18% more sensitive to detecting non-reference conditions, 20% more responsive to an anthropogenic disturbance gradient, and had twice the number of significant bivariate correlations with disturbance variables than the O/E_{50} index derived from the same underlying predictive model. We suggest that the improved performance of BC_A relative to O/E_{50} lies in its ability to detect the addition of alien, translocated, and some native species whose traits allow them to persist or thrive in degraded conditions, and the inclusion of low prevalence taxa that may be sensitive to mild levels of disturbance. Given that generation of the BC_A index requires no further information than already provided by traditional multivariate predictive models, we recommend its inclusion into bioassessment programs that use multivariate fish based indices.

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1. Introduction

Ecosystem health assessments are increasingly being used to understand the level of human related impact on aquatic systems (Bunn et al., 2010; Davies et al., 2010) and in association with this there is a need for the development of reliable and sensitive tools that can be used to undertake such assessments. Biotic indices based on the taxonomic composition of fish assemblages are commonly used to determine ecological status or ‘river health’, diagnose stressors and underpin sound stream management decisions (e.g. Hawkins et al., 2000; Bunn et al., 2010). Ideally, biotic indices provide reliable empirical relationships with important gradients of anthropogenic disturbance to stream ecosystems (Walsh, 2006) while accounting for natural environmental variation. Most stream bioassessment programs rely on a reference condition approach to achieve this, using either multimetric or multivariate methods (Reynoldson et al., 1997; Stoddard et al., 2006).

The multivariate approach involves predicting the taxonomic composition at a test site as if it were in an unimpacted state, typically modelled from data collected from a regional pool of reference (minimally impacted) sites (Norris and Hawkins, 2000). The observed taxonomic composition at a test site is then compared

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to that predicted to occur by a model. The most common output of this is the taxonomic completeness index, that is, the ratio of observed to expected species (O/E) (e.g. Joy and Death 2002). As multivariate methods inherently account for natural variation, and provide 'site-specific' reference condition as a benchmark, they have become an increasingly popular method globally (Norris and Hawkins, 2000). Additionally, the outputs of multivariate models such as the River Invertebrate Prediction and Classification System (RIVPACS) can provide different information to stream managers when interrogated at different levels. For example, the O/E summary index enables comparison among sites in an assessment area, while the predicted probabilities of individual taxa can be used to identify management targets or aid diagnosis of key stressors through post hoc analyses (Norris and Hawkins 2000; Kennard et al., 2006a).

Despite the popularity of the O/E index, it has some perceived drawbacks when implemented using the standard RIVPACS approach and many of its derivatives. First, a community classification approach using discriminant function analysis (DFA) is often used to predict taxa occurrence probabilities (E). This can be limiting because of its fairly strict statistical assumptions, lack of flexibility in fitting data (e.g. using linear functions as opposed to more flexible machine learning approaches), and supposition that discrete assemblages rather than individual taxa are shaped by environmental gradients (Olden et al., 2006). Second, O/E indices usually only consider prevalent taxa such as those predicted to occur above a 50% probability of occurrence threshold (e.g. Smith et al., 1999; Hawkins et al., 2000; Poquet et al., 2009). This is done to increase the precision of the O/E predictions (Poos and Jackson, 2012), but at the potential cost of omitting rare taxa which may be responsive to subtle levels of disturbance (Cao et al., 2001). This practice may also lead to low numbers of expected species in some situations (Rose et al., 2016) and imprecise estimates of ecological condition if the indicator group has few taxa (Smith et al., 1999). Third, the O/E index can be insensitive to changes in assemblage composition that do not affect taxa richness (Chessman et al., 1999; Van Sickle, 2008). Finally, O/E is concerned only with predictions of species presence and omits potentially useful information regarding predicted absences.

These latter points are particularly relevant to fish assemblages, which are rapidly undergoing homogenisation at a global scale owing to the invasion of alien species coupled with the decline of locally native species (Olden et al., 2008). The early stage of homogenization involves species addition, and O/E which considers only loss of predicted taxa, is unable to detect this. O/E would be able to detect the local extinction of 'expected' native species during the later stages of homogenisation (albeit, potentially only those predicted to occur above a specified probability threshold, often 0.5), but this would render the index an ineffective early warning indicator. Alternative indices that incorporate alien fish (e.g. sample proportion abundance of alien species) are responsive and reliable indicators of anthropogenic disturbance to streams (Kennard et al., 2005), but are also unable to directly reflect the degree of faunal homogenization by accounting for both species losses and gains.

Two recent advances in stream bioassessment can address these drawbacks and increase the sensitivity of multivariate indices to detect stream impairment using fish indictors. First, the use of alternative modelling strategies that do not use a classification step, such as multi-species response models and single species ensemble models, can address the statistical limitations of the traditional DFA approach and increase model accuracy (Rose et al., 2016). Second, use of the BC biotic index, an adaptation of Bray-Curtis distance (Van Sickle, 2008) has been shown to increase stressor detection sensitivity compared with the O/E index for a range of indicator taxa (Van Sickle, 2008; Walsh et al., 2010, but see Jyväsjärvi et al., 2011). BC is sensitive to apparent impairment signals from taxa with low prediction probabilities (Van Sickle, 2008), and therefore may be responsive to mild levels of disturbance. It can also detect increases in the prevalence of tolerant native species and the addition of translocated or alien species that may be both an indicator of anthropogenic stress and a cause of declining native fish populations.

Even though the BC index offers apparent advantages over the O/E index (Van Sickle, 2008), it has received little attention for fish indicators. In the present study, we tested whether a BC index that incorporated alien and translocated fish species is more sensitive to detecting anthropogenic disturbances than indices of taxonomic completeness (O/E_{50}). We also tested two other indices currently used in the Ecosystem Health Monitoring Program (EHMP) in South-east Queensland, Australia, namely the percentage of native species expected (Kennard et al., 2006b) herein termed 'PONSE' and the proportion of alien species (Kennard et al., 2005) herein termed 'PropAlien'. A secondary aim was to assess how these indices responded to different types of anthropogenic disturbance.

2. Methods

2.1. Study area and fish sampling methods

The study area includes streams in sub-tropical eastern Australia extending from the Mary River south to the Clarence River and encompassing the EHMP assessment area (Fig. 1). It occurs within the eastern biogeographic province based on freshwater fish distribution (Unmack, 2001), and represents a transitional zone for tropical and temperate species (Pusey et al., 2004). The climate ranges from cool-temperate near the Great Dividing Range on the western margin to sub-tropical along the eastern coastal margin. Rainfall and stream flows are generally highest during summer and autumn, although many of the streams exhibit highly variable flow, both seasonally and inter-annually (Kennard et al., 2010).

Fish assemblages were sampled at 128 'least disturbed' reference sites distributed widely throughout the study area (see Rose et al., 2015) in the post-wet season (autumn/winter) of 2013. Sites were sampled using a standardised single-pass electrofishing protocol (EHMP, 2008), which yields reliable estimates of species presence-absence. On average (±S.E), sites were electrofished for 1087 ± 16 s of power-on time and over a site length of 98 ± 2m.

2.2. Reference condition ensemble model construction and validation

We constructed ensemble models (Thuiller et al., 2009) for each of 23 native fish species from the reference site dataset previously described (Fig. 1) using the methods and GIS-based predictor variables outlined in Rose et al. (2016) (see Supplementary Appendix A for a description of the predictor variables used). Ensemble models combine projections of different model algorithms and initial conditions to provide more robust predictions than from a single model algorithm. Ensemble models were used instead of alternative modelling approaches as they were demonstrated to have the highest predictive performance in our study area (Rose et al., 2016). Briefly, ensemble model predictions were calculated for each species using the arithmetic mean of prediction probabilities of the best performing of 50 5-fold cross-validated candidate models, with models being retained on the basis of a high true-skill statistic (TSS – See Allouche et al., 2006). Candidate models were generated using 5 modelling algorithms (general linear models, boosted regression trees, multivariate adaptive regression splines, artificial neural networks and random forest) and 10 modelling runs. Each modelling run is based on different initial conditions generated from a randomised 80-20% data split for model train-

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