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Application of neural networks to quantify the utility of indices of biotic integrity for biological monitoring

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ABSTRACT

Indices of Biotic Integrity (IBIs) or multimetric indices have been developed as an approach for monitoring and evaluating biological condition of aquatic organisms. Quantitative evaluations of IBIs to determine whether they can explicitly link environmental condition with anthropogenic activities are needed to effectively use them in management. Analytical approaches using supervised neural networks are potentially powerful techniques to evaluate IBIs. The goal of this study was to evaluate the use of neural networks to identify ecosystem characteristics related to IBI response and to explicitly quantify relationships between variables using sensitivity analyses. An aquatic macrophyte-based IBI developed for Minnesota lakes was used as an example. The study was particularly interested in the usefulness of neural networks to highlight key predictors of IBI performance and to be used as a technique to evaluate multimetric index performance in other systems or regions. Neural networks made accurate predictions of overall IBI scores using an independent dataset, whereas predictive performance of the models varied for individual metrics. Bootstrap analyses to evaluate the effects of different training data on model performance indicated that predictions were highly sensitive to the training data. More conventional modeling techniques, such as multiple regression, performed similarly in predicting IBI scores, although diagnostic tools developed for neural networks provided novel insight into variables influencing IBI response. We suggest that neural networks have the ability to quantify ecological relationships that affect biotic integrity, but the statistical uncertainty associated with multimetric indices may limit the use of predictive models to infer causation. Accordingly, the statistical properties of multimetric indices should be carefully evaluated during index development, with specific attention given to the diagnostic capabilities of individual metrics.

Abbreviations: AIC, Akaike's Information Criterion; CWA, Clean Water Act; EMFL, relative frequency of emergent or floating-leaf species; GAM, Generalized Additive Models; IBI, Index of Biotic Integrity; LITT, percentage of littoral area vegetated; MAXD, maximum depth of plant growth; MLR, multiple linear regression; MNDNR, Minnesota Department of Natural Resources; NMSE, normalized mean square error; OVER, number of species with a frequency occurrence of >10%; SENS, relative frequency of sensitive species; SUBM, relative frequency of submersed species; TAXA, number of native taxa; TOLR, relative frequency of tolerant species; VIF, Variance Inflation Factors; WFD, Water Framework Directive.

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1. Introduction

Broad initiatives to identify and remediate stressors that affect aquatic habitat have been implemented under the United States Clean Water Act (CWA) and the European Water Framework Directive (WFD) (Pollard and Huxham, 1998; Barbour et al., 2000). Both initiatives define conditions of aquatic systems that are beneficial of or supportive for aquatic life. Such systems maintain ecological integrity or 'good surface water status' so that the structure or function are comparable to that of natural habitat for the same region (Karr et al., 1986; Pollard and Huxham, 1998). A primary focus on monitoring and evaluating aquatic organisms as integrative indicators of ecological condition has facilitated the creation of numerous ecological indices that support management of healthy aquatic systems. In particular, multimetric indices, such as the Index of Biotic Integrity (IBI, Karr, 1981; Karr et al., 1986), provide an approach for documenting components of biological systems that signal the effects of human-induced stressors. Biological signals form the basis for defining condition and are diagnostic of particular stressors that contribute to environmental degradation (Karr and Chu, 1999).

IBIs have been developed for different aquatic systems such as streams and rivers (Karr, 1981; Barbour et al., 1996), lakes (Drake and Pereira, 2002; Beck and Hatch, 2009), and wetlands (DeKeyser et al., 2003; Miller et al., 2006) and have incorporated fish (Karr, 1981; Minns et al., 1994), macroinvertebrates (Kerans and Karr, 1994; Barbour et al., 1996), plankton (Lougheed and Chow-Fraser, 2002), or aquatic vascular plants (Miller et al., 2006; Beck et al., 2010). IBIs can form the basis of biological standards that identify high-quality systems for protection or degraded systems that require restoration or remediation. An IBI relies on multiple metrics that are scored and summed to obtain an overall score. Metrics quantify aspects of the structure or function of the system that respond to environmental variation (Karr and Chu, 1999). Although an IBI score is used to identify impairments, individual metrics can be diagnostic of specific stressors that affect ecological integrity (Norton et al., 2000). Metric selection is, therefore, a critical component of IBI development that ensures the index is capable of providing useful information for resource managers. For example, metrics may be selected from a large candidate pool during IBI development if they exhibit a sufficient range of values among study sites, high signal to noise ratios (i.e., high variance between-, low variance within-sites), and a unimodal response across a gradient of human disturbance (Whittier et al., 2007).

A distinct advantage of the IBI framework is flexibility that allows adaption for use in regions with different biological communities. Additionally, Karr and Chu (1999) advocate the IBI as a useful tool for evaluating complex environmental systems that allows individuals without specialized expertise to understand overall condition as a basis for informing resource management decisions. Despite these advantages, multimetric indices have been criticized for their potential to combine and, therefore, 'lose' information through the additive combination of individual metrics (Suter, 1993; Radomski and Perleberg, 2012). Conversely, Karr and Chu (1999) maintain that overall IBI scores establish a basis for further investigation of impaired systems using individual metrics as multiple lines of evidence for defining impairment. However, no consensus exists regarding the explicit contribution of metrics for their combinatorial or additive effects on indications of biotic integrity from overall IBI scores. Although both metrics and IBI scores can guide management, the extent to which the two interact remains questionable. For example, is there an actual correspondence between a low IBI and specific metrics that identify cause of impairment? Lack of agreement on the utility of information provided by an IBI and its metrics may stem from inadequate techniques for evaluating index performance in a multivariate context.

An inadequate understanding of the statistical properties of an IBI may further complicate understanding of index performance. Fore et al. (1994) developed a model of IBI scores to show that conventional statistical techniques, such as analysis of variance or regression, were appropriate for evaluating an IBI for data consistent with the assumptions of the central limit theorem. However, the analysis did not address the effect to which individual metrics may combine or interact to influence overall IBI performance. For example, metrics may be based on count data, others may be uniformly distributed, or others may have skewed distributions. The additive effects of metrics with different underlying distributions may influence interpretation of the performance of an IBI. Additional research has investigated effects of sampling uncertainty on the IBI (Dolph et al., 2010) and the effect to which rare species influence metric and IBI scores (Wan et al., 2010). No investigations have focused on multivariate techniques to understand the effects of metric interactions on indications of biotic integrity. More exhaustive methods for evaluating IBI performance should be implemented if the assumption is that both IBI scores and constituent metrics represent information that affects decision-making.

Analytical techniques that take advantage of complex computational algorithms may provide the most practical approach for evaluating multivariate response of an IBI. Specifically, neural network models use computer-based learning techniques that mimic the neuronal structure of the human brain (Garson, 1991; Goh, 1995; Ripley, 1996). Assumptions about the statistical distributions of response variables necessary for more conventional modeling techniques are relaxed for neural networks. Additionally, neural networks are capable of handling noisy and imprecise information, which is common in ecological datasets. Applications of neural networks for ecological and water resource management have increased because of the flexibility of available approaches (Lek et al., 1996; Maier and Dandy, 2000; Olden and Jackson, 2002). Modeling IBI performance with neural networks has included limited examples using unsupervised approaches for pattern recognition (Manolakos et al., 2007) and an evaluation of supervised approaches to predict stream IBI scores (Novotny et al., 2009). No studies have evaluated the use of neural networks to model multivariate response of metrics as a basis for understanding IBI scores. Additionally, no research has evaluated the uncertainty associated with neural network predictions of biotic integrity.

The goal of this study was to apply supervised neural networks to identify ecosystem characteristics linked to biotic integrity and to explicitly quantify relationships between variables (i.e., relative importance, non-linearity) using sensitivity analyses. A macrophyte-based IBI developed for Minnesota lakes was used as an example. Specifically, we focus on two questions: (1) Can neural networks identify lake characteristics with reasonable precision that are related to overall IBI scores or individual metrics? (2) If so, do changes in IBI scores or individual metrics indicate response to stressors that influence biotic integrity? First, methods for developing neural networks to model and predict IBI response are described. Second, neural networks are used to quantify the specific relationships between lake characteristics and IBI response, with particular emphasis on methods for quantifying uncertainty and evaluating index sensitivity to gradients in lake characteristics. Finally, we evaluate the use of conventional statistics (e.g., linear regression) to model IBI scores to determine whether neural networks improved predictive abilities. For all analyses, both natural lake characteristics and anthropogenic variables were evaluated to determine the ability of the IBI to indicate responses to stressors in the context of natural variation. Lakes were also separated into two groups to evaluate regionally calibrated IBIs relative to a statewide index. We consider these analyses to have direct relevance for lake management in Minnesota, whereas the neural