Minnesota Macrophytes: Linking Aquatic Plants, Lake Health, and Human Activities

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This dissertation is dedicated to Gustavo the cat. He has seen it all.

Abstract

Aquatic plants (macrophytes) are an undervalued but critically important component of Minnesota's lakes. The macrophyte Index of Biotic Integrity (IBI) was developed to evaluate lake health using metrics that describe the condition of the aquatic plants. However, a detailed evaluation to determine whether the index can explicitly link lake condition with activities that negatively impact lake resources has not been conducted. This information is necessary before the IBI can be used to develop biological standards required under the federal Clean Water Act. The goal of this dissertation was to develop and implement a framework for identifying the strengths and weaknesses of the index to inform biological assessment. Four chapters describe research to fulfill this goal. The first chapter identifies comparable groups of lakes using a set of environmental variables that influence macrophyte community composition. The second chapter describes the development and application of semi-automated techniques for quantifying potential stressors of aquatic macrophytes in nearshore areas of lakes, such as docks and boat lifts. The third chapter provides a complementary analysis to chapter two by examining the relationships of shoreline development at different spatial scales with metrics describing macrophyte richness. The fourth and final chapter develops modeling techniques to quantify the relative effects of multiple stressors on the IBI. Specifically, I have used artificial neural network models that can 'learn' inherent data structures and are especially useful for modeling noisy data with non-linear relationships. Outcomes from my dissertation will inform management agencies on the most appropriate use of the index, which will ultimately facilitate the protection and restoration of Minnesota's lakes.

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List of Acronyms

AIC Akaike Information Criterion
ANOVA analysis of variance
CPI Crop Productivity Index
CWA Clean Water Act
DEM Digital Elevation Model
DN digital number
EMFL relative frequency of emergent and floating-leaf species
GAM Generalized Additive Models
GDD Growing Degree Days
GIS Geographical Information System
GLM Generalized Linear Models
GLMM Generalized Linear Mixed Models
IBI Index of Biotic Integrity
LIDAR Light Detection and Ranging
LITT percentage of littoral vegetated
MAXD maximum depth of plant growth at 95% occurrence
MLR Multiple Linear Regression
MNDNR Minnesota Department of Natural Resources
MRPP multiple response permutation procedure
NAIP National Agricultural Imagery Program
NIR near infrared
NMS nonmetric multidimensional scaling
NMSE normalized mean square error
OVER number of species with frequency occurrence $> 10\%$
PCA principal component analysis
pRDA partial redundancy analysis
SDI Shoreline Development Index
SENS relative frequency of sensitive species
SUBM relative frequency of submersed species
TAXA number of native taxa
TOLR relative frequency of tolerant species
TSI trophic state index
VIF Variance Inflation Factors
WFD Water Framework Directive

Prologue

The 1972 amendments to the Federal Water Pollution Control Act, commonly referred to as the Clean Water Act (CWA; 33USC1251), requires states, tribes, and territories to develop appropriate methods for protecting and restoring surface waters. Initial approaches to address these requirements primarily focused on the control of specific pollutants, such as nitrogen and phosphorus, through the use of technology-based standards. Although these efforts have been successful in reducing 'end-of-pipe' or point-sources of pollution, methods for protecting biological resources have not been as extensively implemented. In particular, chemical and physical standards may be insufficient for protecting aquatic habitat and biological communities. These limitations prompted the proposal of the Index of Biotic Integrity (IBI) that provided a regionally-specific framework for evaluating the health of aquatic organisms (Karr, 1981; Karr et al., 1986). An IBI is a multimetric index that uses aquatic organisms as indicators of environmental condition. Each metric represents an aspect of the structure or function of the aquatic community that responds in a predictable manner to environmental changes.

IBIs have recently been used in the United States to develop enforceable standards for aquatic resources. An IBI score can be used to identify critical thresholds that define biological impairments, whereas a disaggregation of individual metrics may indicate causes of poor environmental condition. The aquatic taxa that form the basis for determining an IBI is of primary importance given the trophic relationships that biological communities may support or depend on. The IBI approach was first developed using fish as indicators given their relation to stakeholders and the availability of extensive life history information (Karr, 1981). Other organisms that exhibit changes to environmental condition have also been proposed for use with IBIs. In particular, aquatic plants (macrophytes) have recently been proposed for biological monitoring in lake ecosystems (Nichols et al., 2000; Beck et al., 2010; Radomski and Perleberg, 2012; Kanninen et al., 2013). Macrophytes represent a historically under-appreciated component of lake trophic networks that support multiple aquatic resources. The variation among macrophyte communities to changing environmental conditions provides sufficient information for evaluating biological health (Melzer, 1999; Rasmussen and Anderson, 2005).

Several IBIs have been developed for use in Minnesota and include indices for stream monitoring using fish (Niemela and Feist, 2000, 2002) and invertebrates (Chirhart, 2003; Genet and Chirhart, 2004), wetland monitoring using invertebrates and plants (Gernes and Helgen, 2002; Genet and Bourdaghs, 2006), and river monitoring using macrophytes (Moore et al., 2012). Development of IBIs for lakes has not progressed as rapidly as efforts for other aquatic systems. The application of IBIs for lake monitoring is a relatively new concept and several unique challenges must be addressed prior to index development (Beck and Hatch, 2009). For example, comparable groups of lakes with similar biotic communities in the absence of anthropogenic influences must be identified, sufficient knowledge about the types and extent of human-induced stressors must be quantified, and variation in biotic response attributed to anthropogenic influences must be characterized. Two IBIs for Minnesota lakes have recently been developed and current research objectives seek to address the extent to which the indices accommodate the above challenges. The fish-based IBI (Drake and Pereira, 2002) was developed for small lakes in central Minnesota and has since been validated for use in other lake types (Drake and Valley, 2005). More recently, a macrophyte-based IBI has been developed as a complementary and alternative approach for lake monitoring (Beck et al., 2010).

The macrophyte-based IBI was developed using a dataset of 97 lakes that were similar to those used to develop the fish-based IBI. Lake characteristics varied such that a gradient of productivity and bathymetric changes from southern to northern Minnesota were observed. Macrophyte communities also exhibited changes across a latitudinal gradient related to variation in lake characteristics. Consequently, IBI scores reflected changes in macrophyte community composition related to both natural variation and anthropogenic stress variables (Beck et al., 2010). The index was composed of seven metrics adapted from Nichols et al. (2000): 1) maximum depth of plant growth at 95% occurrence (MAXD), 2) percentage of littoral vegetated (LITT), 3) number of species with frequency occurrence $> 10\%$ (OVER), 4) relative frequency of submersed species (SUBM), 5) relative frequency of sensitive species (SENS), 6) relative frequency of tolerant species (TOLR), and 7) number of native taxa (TAXA). Chapter 4 introduces a new metric, the relative frequency of emergent and floating-leaf species (EMFL). The responsiveness of individual metrics to gradients in environmental condition suggested that the macrophyte IBI could be used complementary to the fish-based IBI to evaluate lake health. However, the macrophyte-based IBI was designed as a preliminary index with further validation and testing necessary before implementation in statewide monitoring. Several questions remained regarding the strengths and weaknesses of the index for evaluating biotic integrity.

The overall goal of this dissertation was to develop and implement a framework for evaluating the macrophyte IBI to inform its use in biological monitoring, with emphasis on quantitative methods that can be adapted for use in other systems or regions. The analyses build extensively on information provided in Beck et al. (2010) by expanding the IBI to a larger dataset and addressing broader questions designed to facilitate use of the index for biological monitoring. The analyses address the following:

1. What lakes types can the index be applied to with confidence (chapter 1)?
2. How well does the index distinguish between signal and noise (chapters 1 and 4)?
3. Can information on stressors be quantified with certainty (chapters 2 and 4)?
4. What stressors primarily influence index response (chapters 3 and 4)?
5. How appropriate is a multimetric index for characterizing effects of multiple stressors (chapter 4)?

A substantial portion of the dissertation focuses on quantifying stressors of macrophyte communities to better understand sources of variation in biological response. Specifically, I present methods for quantifying shoreline development and provide an assessment of the potential effects on macrophyte communities at different spatial scales.

Data and chapter summaries

Data used for all analyses were obtained from the Minnesota Department of Natural Resources (MNDNR) and included 332 lakes throughout Minnesota, excluding chapter 1, which used the original dataset of 97 lakes described in Beck et al. (2010). Data for each lake included a point-intercept survey (Madsen, 1999) that was used to calculate IBI and metric scores. Supporting data for each lake were obtained primarily from public datasets, such as Geographical Information System (GIS) shapefiles available on the MNDNR Data Deli (MNDNR, 2012a) or water quality information from online databases (i.e., MNPCA, 2012).

The goal of Chapter 1 is to identify environmental characteristics of lakes that naturally influence macrophyte index response to establish a preliminary lake classification scheme for biological assessment. Flexible beta classification was used to identify comparable groups of lakes. The variation in macrophyte index response attributed to anthropogenic stress variables before and after lake clustering was also evaluated. Comparable groups of lakes identified through clustering approximated ecoregion boundaries described in (Omernik, 1987), which could be used to develop regionally-specific scoring criteria for the index. In particular, IBI scoring methods that are specific for northern or southern groups of lakes should be developed. IBI scores evaluated within comparable groups of lakes may exhibit reduced variation related to natural lake characteristics, potentially improving the signal of biological response to anthropogenic stressors.

Chapter 2 describes the development and application of semi-automated techniques for quantifying potential stressors of aquatic macrophytes in nearshore areas, such as docks and boat lifts, using high-resolution aerial photos. The programmatic code used to analyze the images is provided in listings B.1 and B.2. The image analysis techniques were used to quantify shoreline development for 4,261 lakes managed by MNDNR. The resulting information represents the first statewide dataset describing dock quantity and cover. Overall accuracy after post-processing was 98.4%, suggesting the data provide an accurate proxy of shoreline development. Processing time was also 74% more efficient than manual digitization. Lakes in the central portion of the state and near the Twin Cities metropolitan area had much higher shoreline development than other areas and could be prioritized for habitat restoration activities.

Chapter 3 provides a complementary analysis to chapter 2 by examining the relationships of shoreline development at different spatial scales with metrics describing macrophyte richness. Although the macrophyte IBI is not evaluated in chapter 3, the results provide novel information on the effects of shoreline development on macrophyte communities. The response of richness-based metrics to shoreline development was evaluated at two different spatial scales. First, the between-lake effects of shoreline development was evaluated for 1,444 lakes to determine whether dock density was related to whole-lake measures of macrophyte richness. Second, three lakes were used to evaluate within-lake effects of shoreline development by modeling the relationships between macrophyte metrics and distance of survey points from the nearest structure. Results suggested that increasing shoreline development is associated with fewer emergent-floating and sensitive species at the whole-lake scale. Within-lakes, points farther from structures were more likely to have higher species richness and presence of sensitive species. Overall, additional evidence is provided that suggests shoreline development is an important stressor that could be considered when evaluating lake health.

Chapter 4 describes the use of modeling techniques to quantify the effects of multiple stressors on the IBI. Specifically, supervised neural networks were used to characterize IBI and metric response in a multivariate context for the purpose of identifying key predictors. Neural networks were developed for all 332 lakes, as well as separate models for northern and southern groups to determine whether regionally-specific IBIs exhibited unique responses to anthropogenic stressors. Neural networks developed for the entire dataset made accurate predictions of IBI scores, whereas models for the northern and southern groups had poor performance. Additionally, bootstrap analyses indicated models were highly sensitive to the training data, although consistent relationships between some variables were observed. Neural networks were also compared with conventional models (e.g., linear regression). Similar predictive performance of IBI scores was obtained using different modelling approaches.

The final chapter concludes with a specific suggestion that statistical properties of multimetric indices be carefully evaluated prior to index development. This suggestion is elaborated here to emphasize a primary conclusion of the dissertation. The analyses have shown that neural networks, in addition to more conventional models, have limited capabilities in predicting IBI and metric scores. Accordingly, the inability to relate explanatory variables to the IBI and individual metrics may be related to the statistical properties of multimetric indices, rather than the method used to model index response. Although others have evaluated the statistical characteristics of multimetric indices (e.g., Fore et al., 1994), researchers and managers should be cautious in using IBIs to guide decision-making. The results suggest that considerable uncertainty exists between the response of metrics to explanatory variables and how the metrics interact to influence overall IBI scores. This uncertainty in IBI response may relate primarily to the additive effects of combining individual metrics with different underlying distributions.

An IBI may have two distinct and potentially conflicting purposes that may not be simultaneously achieved in biological monitoring. These two purposes relate to the primary rationale of a biological index and the need to have statistical confidence in an index for making resource management decisions. Karr et al. (1986) suggests that the complexity of biological systems requires the use of multiparameters to evaluate biotic integrity. The resulting index combines information from these multiparameters to enable people without specialized experience to make informed resource management decisions (Karr and Chu, 1999). Although I do not disagree with the rationale, I believe that the combination of multiparameters to summarize biological complexity may confuse or even prevent informed decision-making. Resource management decisions will not be informed if the effects of specific explanatory variables on individual metrics and overall IBI scores cannot be determined with confidence. I have shown that multiple methods may not fully quantify these effects. An IBI represents a unique situation where its primary function to summarize biological complexity may sabotage its utility to inform decision making. As such, the statistical properties of an IBI may prevent resource managers from obtaining reliable information about causation. I conclude that the characteristics of multimetric indices be carefully evaluated prior to index development. Quantitative links between explanatory variables, individual metrics, and overall IBI scores should be empirically determined prior to implementation of an index to inform decision-making.

Format of the chapters

Each chapter was prepared as a manuscript for publication in the primary literature. At the time of writing, chapter 1 is published in Aquatic Botany (Elsevier, Beck et al., 2013a), chapter 2 is published in the ISPRS Journal of Photogrammetry and Remote Sensing (Elsevier, Beck et al., 2013b), and chapter 3 is in review in Lake and Reservoir Management (Taylor and Francis). Chapter 4 is currently in preparation for submission to Ecological Modelling (Elsevier). The dissertation chapters may differ slightly from those published in the primary literature. Published chapters are reproduced in the dissertation under the author's copyright agreement for personal use. Co-authors include Lorin Hatch (chapters 1 to 4), Jason Vinje (chapter 2), Bruce Vondracek (chapters 1 to 4), and Bruce Wilson (chapter 4). The plural pronouns "we" or "our" are used rather than the singular "I" or "my" in reference to co-authorship.

Chapter 1

Environmental clustering of lakes to evaluate performance of a macrophyte index of biotic integrity

Abstract

Proper classification of sites is critical for the use of biological indices that can distinguish between natural and human-induced variation in biological response. The macrophyte-based Index of Biotic Integrity (IBI) was developed to assess the condition of Minnesota lakes in relation to anthropogenic stressors, but macrophyte community composition varies naturally across the state. The goal of the study was to identify environmental characteristics that naturally influence macrophyte index response and establish a preliminary lake classification scheme for biological assessment (bioassessment). Using a comprehensive set of environmental variables, we identified similar groups of lakes by clustering using flexible beta classification. Variance partitioning analysis of IBI response indicated that evaluating similar lake clusters could improve the ability of the macrophyte index to identify community change to anthropogenic stressors, although lake groups did not fully account for the natural variation in macrophyte composition. Diagnostic capabilities of the index could be improved when evaluating lakes with similar environmental characteristics, suggesting the index has potential for accurate bioassessment provided comparable groups of lakes are evaluated. Relevant variables to consider for improving biological assessment and additional approaches for further validation of the index are suggested. Although this information is applicable to Minnesota, this approach is relevant for any agency concerned with accurate bioassessment.

1.1 Introduction

Biological assessment (bioassessment) is the use of living organisms to evaluate the condition or health of an aquatic environment for the purpose of guiding resource management (Karr and Chu, 1999). A popular method for bioassessment is a multimetric approach using an Index of Biotic Integrity (IBI, Karr et al., 1986). A recent summary of bioassessment programs in the United States indicated that 68% of states, tribes, territories, and interstate commissions utilize or are developing multimetric indices (US Environmental Protection Agency, USEPA, 2002). Initiatives under the European Union Water Framework Directive (WFD) have also focused on the development of multimetric indices for bioassessment (Stelzer et al., 2005; Penning et al., 2008). Multimetric indices provide information about biological condition by integrating ecological, functional, and structural aspects of aquatic systems using metrics that respond in a predictable manner to human-induced stress. Higher IBI scores are indicative of systems with less environmental degradation and higher biotic integrity. Useful biological indices more clearly identify biological response to anthropogenic stressors and exhibit minimal variation attributed to environmental characteristics, such as lake depth or watershed size (Karr and Chu, 1999). An aquatic macrophyte-based IBI has recently been developed for lakes in Minnesota, USA (Beck et al., 2010), although little information is available describing the unique roles of environmental characteristics in influencing index behavior.

Aquatic macrophytes are particularly well-suited for bioassessment because of documented changes in response to environmental condition (Genkai-Cato and Carpenter, 2005; Penning et al., 2008; Mackay et al., 2010) and roles in structuring the biological, chemical, and physical characteristics of lakes (Jeppesen et al., 1998; Cross and McInerny, 2006). However, several biogeochemical pathways shape the structure and function of macrophyte communities (Barko et al., 1982; Vestergaard and Sand-Jensen, 2000; Mackay et al., 2003; Alexander et al., 2008), and the ability to distinguish signals (anthropogenic-induced variation) from noise (environmental, natural variation) is challenging (Cheruvelil and Soranno, 2008). For example, environmental variables that affect macrophyte communities are related to lake characteristics (e.g., littoral slope, surface area, water chemistry, sediment) (Moyle, 1945; Vestergaard and Sand-Jensen, 2000), regional climate patterns (e.g., temperature, precipitation, growing season length, wind) (Barko et al., 1982; Keddy, 1982; Rooney and Kalff, 2000), and watershed characteristics (e.g., soils, landscape position, land use/cover) (Alexander et al., 2008; Cheruvelil and Soranno, 2008; Beck et al., 2010). These variables can interact to confound interpretations of macrophyte distributions (Cheruvelil and Soranno, 2008; Mikulyuk et al., 2011). A common approach for bioassessment is to identify groups of similar waterbodies that minimize natural variation in biological communities to accurately characterize response of biota to stressors (Karr and Chu, 1999). Recent development of macrophyte-based indices necessitates the classification of waterbodies that considers relevant biogeochemical pathways.

The ability of the Minnesota macrophyte-based IBI to distinguish biological response to anthropogenic stressors from natural community variation has not been evaluated, nor have comparable groups of lakes been identified that minimize natural variability. The macrophyte IBI consists of seven metrics: maximum depth of plant growth at 95% occurrence (MAXD), percentage of littoral vegetated (LITT), number of species with frequency occurrence $>$ 10% (OVER), relative frequency of submersed species (SUBM), relative frequency of sensitive species (SENS), relative frequency of tolerant species (TOLR), and number of native taxa (TAXA). The macrophyte IBI was developed using a dataset of 97 lakes that were chosen from the same lake classes used to develop the Minnesota fish-based IBI (Drake and Pereira, 2002). The lake classification system used to develop the fish-based IBI identifies lakes with similar fish communities and may be inappropriate for defining groups of lakes with similar macrophyte communities. Additionally, Beck et al. (2010) did not sufficiently evaluate use of the macrophyte IBI on a statewide basis, particularly in the context of macrophyte communities that exhibit considerable natural variation (Moyle, 1945). The identification of comparable groups of lakes for macrophyte bioassessment could improve use of the index to characterize macrophyte response to anthropogenic stressors.

The goal of the study was to identify environmental characteristics that influence macrophyte IBI response as a basis for establishing a preliminary lake classification to improve bioassessment. The objectives were to 1) quantify major sources of natural variation in macrophyte communities in Minnesota glacial lakes, 2) use the quantified environmental variables to identify similar groups of lakes that minimize natural variability in macrophyte response, and 3) evaluate the effectiveness of using similar groups of lakes for improving bioassessment. Throughout, a distinction between environmental and anthropogenic variables is made such that natural variation in macrophyte communities is observed across environmental gradients, whereas macrophyte communities also respond to stressors attributed to anthropogenic variables. Useful biological indices more clearly identify biological response to anthropogenic stressors and exhibit minimal variation attributed to environmental characteristics, such as lake depth or watershed size (Karr and Chu, 1999). To achieve the objectives, we quantify 25 environmental variables that influence natural variability of macrophyte communities. These variables are then used in a clustering analysis to identify similar groups of lakes, followed by ordination to illustrate the relative influence of the environmental variables on the clusters. Lastly, we use both environmental and anthropogenic variables to quantify the proportion of macrophyte response attributed to both types of variables before and after clustering. We hypothesized that anthropogenic stressors would exhibit a larger influence on the macrophyte IBI when evaluating comparable lake groups, suggesting improved capabilities of the index to diagnose biological impairment. Information from the analyses provides a framework for lake classification that has relevance for implementation of macrophyte indices in Minnesota and other regions with comparable data.

1.2 Methods

1.2.1 Survey data and lake characteristics

A dataset of 97 lakes described in Beck et al. (2010) was used to evaluate the response of the macrophyte IBI. Each lake has information for IBI and metric scores obtained from point intercept vegetation surveys (Madsen, 1999). The dataset contains lakes in four ecoregions in Minnesota: the North Central Hardwood Forests ($n = 43$), Northern Glaciated Plains ($n = 6$), Northern Lakes and Forests ($n = 38$), and Western Cornbelt Plains ($n = 10$) (Omernik, 1987, fig. 1.1). Lakes in the northeast are typically deep and dimictic, whereas lakes in the southwest are typically shallow and polymictic. Lakes in the southern and south-western regions of the state are also more nutrient rich, as a result of lake depth, land use, and soil characteristics of the watersheds. Temperature and precipitation rates decrease with latitude and also vary with regional topography. Climate patterns can affect lake characteristics through varying rates of evapotranspiration, runoff, and length of the growing season.

Twenty-five environmental variables were quantified based on their hypothesized effect on the distribution of aquatic plants across multiple spatial scales (table 1.1). The macrophyte IBI was expected to exhibit variability associated with these environmental variables because comparable groups of lakes for bioassessment of macrophytes have not been identified. The selected environmental characteristics were grouped into three categories: lake, watershed, and climate. Finally, four anthropogenic variables were quantified for use in variance partitioning analyses described in section 1.2.2 (table 1.2).

Lake characteristics

Quantified lake characteristics were surface area, maximum depth, Shoreline Development Index (SDI), and lake elevation. Surface area and maximum depth were obtained from shapefiles provided by the Minnesota Department of Natural Resources (MNDNR, 2012a). SDI was calculated as the ratio of shoreline length to the circumference of a circle of area equal to that of the lake (Wetzel, 2001) and serves as a proxy for habitat variability, i.e., lakes with SDI $\rightarrow 1$ become increasingly circular, whereas lakes with SDI $>> 1$ have increasingly complex shorelines. Elevation is the height of the lake above sea level and was obtained from a Digital Elevation Model (DEM) for Minnesota (MNDNR, 2012a).

Watershed characteristics

Quantified watershed characteristics were watershed area, ratio of watershed area to lake surface area, number of catchments upstream (flow network data from MNDNR, 2012a), watershed elevation range, mean watershed slope, and soil and geological characteristics (see below). Lake watersheds were defined as the continuous area of land drained by the upstream hydrological network, including the land that drains directly into a lake. Watershed elevation range and mean slope were obtained from a statewide DEM (MNDNR, 2012a).

Soil characteristics of lake watersheds can influence the physical and chemical properties of runoff entering a lake (D'Arcy and Carignan, 1997; Wetzel, 2001). Soil characteristics quantified for each watershed were available water capacity, percent clay, liquid limit of soil layer (required water content for mobility), percent organic material, permeability, depth of soil layer, and Crop Productivity Index (CPI, from Natural Resource Conservation Service, NRCS, 2006, 2010). CPI values were obtained from county soil surveys (NRCS, 2010) and describe the suitability of soil types for growing corn as a proxy of natural soil fertility of a watershed.

The type and amount of glacial debris in lake watersheds is related to the topography and overlying soil layers, which can influence limnological characteristics of lakes (Swanson et al., 1988). Moyle (1956) provides a more detailed description of Minnesota geology and effects on lake water quality. Geological characteristics quantified for each watershed were the percent area as glacial outwash, end moraine, ground moraine, stagnation moraine, and other geology (e.g., alluvium or peat). Data were summarized using quaternary geology shapefiles (MNDNR, 2012a) that contain polygons for major glacial lobes (e.g., Superior or Des Moines lobe) and type of debris for each lobe (e.g., ground moraine) present after the most recent glacial period.

Climate characteristics

Quantified climate characteristics were mean July air temperature, mean Growing Degree Days (GDD), mean annual amount of precipitation, and wind effects. Average July air temperature and mean GDD provided an indication of the influence of temperature on aquatic plant growth. Plant growth is influenced by ambient temperature conditions, such that biomass is generally proportional to temperature, which can affect species interactions and shape community dynamics (Barko et al., 1982; Rooney and Kalff, 2000). Mean July temperatures were obtained from shapefile polygons describing mean annual temperatures by month from 1961-1990 (MNDNR, 2012a). The polygon data describe temperatures for discrete regions of Minnesota and were used to interpolate values at each lake. Mean growing degree days and precipitation for each lake were obtained using annual data from 1971-2000 (Lorenz and Delin, 2007; Minnesota Geographic Data Clearinghouse, MGDC, 2007). A base of 10 °C for GDD was considered appropriate given past research on the effects of temperature on growth patterns of macrophytes (Madsen and Brix, 1997).

Wind effects were evaluated using a whole-lake wind index combining wind strength and fetch (*sensu* Cross and McInerny, 2006) using data from 15 weather stations (hourly observations from 2006, U.S. Department of Commerce, USDOC, 2011). Wind indices were obtained by multiplying the percent of time that the wind at the nearest weather station was at each of 16 equidistant radial lines by a measure of wind power for each lake. The product was then multiplied by the length of each radial line from a lake's centroid to the shoreline (i.e., fetch). The final index was the summation of these products (fig. A.1).

Anthropogenic characteristics

Quantified variables describing potential anthropogenic impacts on aquatic plants were the percentage of each lake watershed as agriculture, urban, or forested land, and a lake trophic state index (TSI, Carlson, 1977) (table 1.2). Beck et al. (2010) found that these variables were correlated with macrophyte IBI response, but a detailed analysis of the effects of anthropogenic variables relative to environmental variables was not conducted. TSI values were considered robust measures of the impact of cultural eutrophication because TSI values were significantly correlated with agricultural land use within lake watersheds ($\rho = 0.52$, $p < 0.005$). TSI values were determined from eq. (1.1) such that:

$$\mathrm{TSI} = 10\left(6 - \frac{\log \mathrm{SD}}{\log 2}\right) \tag{1.1}$$

where TSI is a function of water clarity measured as secchi depth (Carlson, 1977). TSI values range from 0–100 with higher values indicating more culturally-eutrophic systems. Secchi depth data were obtained from the Minnesota Pollution Control Agency (MNPCA, 2012). Land use within each watershed was obtained using information from the 2006

National Land Cover Database (Fry et al., 2011) and each land use variable was quantified as the percentage of total watershed area relative to all other land use categories for each lake watershed.

1.2.2 Analyses

Clustering

Flexible beta classification was conducted to identify similar groups of lakes based on the lake, watershed, and climate variables. Flexible beta classification is an agglomerative clustering method that combines a group of elements (i.e., lakes) into clusters by optimizing element properties (i.e., lake characteristics) using measures of dissimilarity and an explicit sorting strategy (Lance and Williams, 1967). Euclidean distances were used to determine dissimilarity between lakes based on lake, watershed, and climate characteristics. We chose Euclidean distance rather than more commonly used Bray-Curtis (Sørensen) measures because the input data did not describe species abundance or presence/absence (i.e., a site by environmental variable matrix was used). To minimize the influence of large values and outliers (Zuur et al., 2007), input variables that departed from normality were monotonically transformed using maximum likelihood estimates of the transformation parameter obtained from Box-Cox methods (Cook and Weisberg, 1999). All variables were standardized from 0–1.

The sorting strategy for flexible beta classification is defined by a single parameter, β, that can vary from -1–1 (Lance and Williams, 1967). Milligan (1989) suggested $\beta =$ -0.5 as an approximate value that balances the alternative clustering behaviors and minimizes the influence of outliers. Groups of lakes were identified using $\beta =$ -0.5 and dendrogram splitting using different height (i.e., similarity) thresholds. Homogeneity among groups was evaluated using multiple response permutation procedures (MRPP, McCune and Grace, 2002). MRPP is a non-parametric approach for evaluating the significance of clustering and is analogous to a multivariate analysis of variance (ANOVA) for parametric data. Additionally, MRPP produces a measure of within-group homogeneity; the 'effect size' or A. Values approaching one indicate group members within each group are identical, whereas values approaching zero indicate group members have no shared characteristics. The optimal amount of clustering was also assessed using a post-hoc variant of MRPP in a stepwise comparison of each group to all other groups (analogous to a post-hoc Tukey-Kramer analysis for parametric data). The `vegdist` and `MRPP` functions of the vegan package (Oksanen et al., 2010), `cutree` function of the stats package, and `agnes` function of the cluster package (Maechler et al., 2005) were used for the clustering analyses in program R (RDCT, 2013).

Ordination

Nonmetric multidimensional scaling (NMS) was used to illustrate the relative influence of the environmental variables on the clusters identified from classification. NMS works well when data are nonnormal, or are on arbitrary, discontinuous or questionable scales (McCune and Grace, 2002). The standardized and transformed variables used for flexible beta classification were used in NMS ordinations as recommended in McCune and Grace (2002, p. 135). Euclidean distances were used as before to define dissimilarity between lakes. A random starting configuration of the sample points was used followed by 100 runs on actual and random data to achieve a stable solution (fig. A.2). Data were randomized after each run to determine whether the ordination produced results that were different than would be expected by chance alone. A stable solution was determined when instability of the stress measure did not vary more than $1e^{-7}$ for the preceding five runs. Stress was defined as a departure in monotonicity in the plot of distances in the original dissimilarity matrix to those in the reduced dimensions of the ordination space. Stress values between 10 and 20 are generally considered satisfactory for inference, with values closer to 10 being more desirable (Clarke, 1993). Outliers were identified based on position in the ordination plots relative to all data points. The appropriate number of axes was evaluated using a screeplot (final stress as a function of number of axes, fig. A.2) and explained variance in the original distances in the dissimilarity matrix by the number of axes in the ordination solution. Ordination results were also evaluated using Spearman rank correlations to compare each NMS axis to the original environmental variables. The clustering results were combined with the ordination plots to identify environmental variables that explained similarity among groups. The `metaMDS` and `stressplot` functions in the vegan package and `Shepard` function in the MASS package were used (Venables and Ripley, 2002; Oksanen et al., 2010).

Variance partitioning

The final analysis was a variance partitioning analysis of anthropogenic and environmental variables. The analysis was conducted using the entire dataset and a smaller subset of lakes identified from clustering (section 1.2.2) to evaluate our hypothesis that anthropogenic stressors may exhibit a larger influence on the macrophyte IBI when evaluating comparable lake groups that minimize environmental variability. Conversely, we expected a relatively larger portion of variance in the metric and IBI scores to be explained by environmental variables when evaluating the entire dataset of 97 lakes. Explanatory variables for the variance partitioning analyses included data matrices for the combined group of environmental variables (**E**, table 1.1) and the combined group of anthropogenic variables (**A**, table 1.2).

Two different approaches were used to partition variance: partial redundancy analysis (pRDA) for metric values and partial Multiple Linear Regression (MLR) for IBI scores (Legendre and Legendre, 1998; Beisner et al., 2006; Zuur et al., 2007). Both approaches were used to evaluate the entire dataset and individual lake clusters. Redundancy analysis is conceptualized as an extension of MLR, such that the approach can be used to evaluate the effects of explanatory variables on a matrix of response variables (a 97 $\times$ 7 matrix of metric values, $\mathbf{Y}$), rather than a single variable in the case of MLR (the vector of IBI scores for 97 lakes, y). Using methods from Beisner et al. (2006) and Zuur et al. (2007), three models for each analysis (pRDA and partial MLR) were developed. The first model used a combined matrix of explanatory variables $\mathbf{A}$ and $\mathbf{E}$, the second used only anthropogenic variables $\mathbf{A}$, and the third used only environmental variables $\mathbf{E}$. Adjusted fractions of variation for each model and simple arithmetic functions were used to partial out fractions of variation of response variables (metric or IBI scores) attributed to 1) the pure effect of anthropogenic variables (pure $\mathbf{A}$), 2) the pure effect of environmental variables (pure $\mathbf{E}$), 3) the effect shared by anthropogenic and environmental variables ($\mathbf{A}$ and $\mathbf{E}$), and 4) the residual effect not attributed to any variables (adapted from Beisner et al., 2006).

Prior to the variance partitioning analyses, principal component analyses (PCAs) were used to reduce the number of explanatory variables in the partial MLR analyses for IBI scores. Axes that explained at least half of the variation in the explanatory matrices were used as input for each model. For the first model that included the combined matrix from $\mathbf{A}$ and $\mathbf{E}$, PCA axes for each matrix were included as both additive and interactive effects. The significance of all models was evaluated using ANOVAs. For the pRDA models, the significance of each model was determined using an ANOVA-like test based on 999 permutations, whereby data were randomized and compared with the original model (Legendre and Legendre, 1998). The functions `rda` and `varpart` of the vegan package (Oksanen et al., 2010) were used for pRDA. A custom function was developed for partial MLR analyses that used the `lm` function as part of the R base package (RDCT, 2013).

1.3 Results

1.3.1 Environmental variables

The lake, watershed, and climate characteristics varied considerably across lakes (table 1.1). In general, lakes varied from deep, large lakes with complex shorelines to small, shallow lakes with simple shorelines. Watersheds ranged in size from small (1.3 km^2) to large (1551.0 km^2) and exhibited a range of soil and geological characteristics. Ten types of glacial debris were present in lake watersheds. End moraine, stagnation moraine, ground moraine, and outwash covered 93% of all watersheds, justifying the grouping of the remaining geological types into an 'other' category. Climate characteristics also varied. Precipitation and temperature (including GDD) were higher in southern areas of the state following expected latitudinal gradients (section 1.2.1). However, precipitation patterns followed an increasing gradient from northwest to southeast, whereas temperature followed an increasing gradient from northeast to southwest. Wind indices varied for each lake, although no pattern was apparent (fig. A.1). In general, the range of IBI scores followed natural environmental gradients from north to south. For example, lakes in the north had higher IBI scores, greater maximum depth, and infertile soils in the watersheds, whereas those in the south had lower IBI scores, shallower depths, and fertile soils.

1.3.2 Clustering

Ten variables were transformed to approximate normality prior to flexible beta classification: catchments upstream, depth, GDD, SDI, surface area, watershed area, watershed to surface area, and organic material content, permeability, and thickness of soil. Visual assessment of lake clusters using β = -0.5 suggested the parameter value was appropriate and minimized the influence of outliers. Two through five lake clusters were obtained by cutting the dendrogram at heights of 40.5, 15.9, 13.1, and 11.3, respectively (fig. 1.2). MRPP results were significant, indicating that the lake groupings between each cluster were more different than would be expected by chance alone. The effect sizes were 0.13, 0.19, 0.23, and 0.27 for two to five groups, respectively, which indicated increasing similarity of lakes within clusters. However, effect sizes were not close to one, indicating relatively high levels of heterogeneity within groups.

The lake clusters were generally partitioned along a north-south gradient and provided an approximation of the Omernik (1987) ecoregions (fig. 1.3). The spatial arrangement for two groups generally combined lakes into 1) the Northern Lakes and Forests and North Central Hardwood Forests ecoregions and 2) Northern Glaciated and Western Cornbelt Plains ecoregions. The spatial arrangement for three groups generally combined lakes into 1) the Northern Lakes and Forests ecoregion, 2) North Central Hardwood Forests ecoregion, and 3) Northern Glaciated and Western Cornbelt Plains ecoregions. The spatial arrangement for four and five groups were less clear as clusters appeared to indicate groups beyond the level of ecoregions.

1.3.3 Ordination

Initial assessment of NMS ordination indicated no outliers in the ordination space. Sequential addition of axes reduced final stress of the ordination at a diminishing rate rather than a clear breakpoint beyond which axis addition provided little improvement (fig. A.2). Therefore, three axes were selected based on a balance between stress and ability to interpret the ordination in three-dimensional space. Three axes had a final stress value of 13.3 and explained 87% of the variation in lakes using the linear fit of distances in the ordination space to those in the original data space. Results using randomized data in a three-dimensional ordination indicated that the actual ordination solution was significant ($p < 0.05$, fig. A.2).

Three lake clusters obtained from flexible beta classification (top-right, fig. 1.3) were used to evaluate the ordination results because these clusters most closely approximated the ecoregions defined in Omernik (1987). The clusters were clearly separated along ordination axes (figs. 1.4 and A.3). Groups 1 (northern group - green) and 2 (central group - yellow) were separated from group 3 (southern group - red) along axis 1. Group 1 was separated from group 2 along axis 3. Watershed characteristics, particularly geology, were important in explaining variation among the lakes as indicated by the length and orientation of the vectors. Stagnation moraine and ground moraine were opposed with outwash and end moraine along axis 1. End moraine was opposed with all geology variables along axis 2. Additionally, number of catchments upstream was an influential variable that was negatively correlated with axis 2. Soil characteristics provided additional explanatory information as indicated by Spearman rank correlations (table 1.3). Clay had the strongest positive correlation with the first axis ($\rho = 0.86$), whereas permeability had the strongest negative correlation ($\rho =$ -0.83). Other soil characteristics were strongly correlated with axis 1 and included liquid limit ($\rho = 0.82$), available water capacity ($\rho = 0.62$), and CPI ($\rho = 0.83$). Watershed slope had the strongest positive correlation with the second axis ($\rho = 0.42$), whereas number of catchments upstream had the strongest negative correlation ($\rho =$ -0.85). Lake depth had the strongest positive correlation with the third axis ($\rho = 0.55$), whereas outwash had the strongest negative correlation ($\rho =$ -0.37).

Qualitative evaluations of IBI scores using size of the data points in figs. 1.3, 1.4 and A.3 indicated clear spatial trends and relationships with ordination axes. The distribution of IBI scores in fig. 1.3 indicated a decline in scores towards southern Minnesota. Additionally, group 1 (northern group - green) had the highest IBI scores, group 2 (central group - yellow) had intermediate IBI scores, and group 3 (southern group - red) had the lowest IBI scores. Figure 1.4 indicated IBI scores decreased with increasing values of the first axis. IBI scores were also positively correlated with the third axis, but not the second axis.

1.3.4 Variance partitioning

Each fraction of variation for the response variables using the full set of 97 lakes was significant ($p < 0.05$), with the exception of the pure effect of $\mathbf{E}$ on IBI scores. The full pRDA model using both $\mathbf{A}$ and $\mathbf{E}$ explained 62% of the variance in metric values, whereas the full MLR model explained 70% of the variance in IBI scores (fig. 1.5). For both models, the pure effects of $\mathbf{A}$ and $\mathbf{E}$ were small compared to their shared effects, indicating substantial internal correlations between the two matrices of explanatory variables. The fractions of variation shared by $\mathbf{A}$ and $\mathbf{E}$ were 49% for the metric values and 54% for the IBI scores. The pure effects of $\mathbf{E}$ exceeded the pure effects of $\mathbf{A}$ for the metrics, whereas the opposite was true for the IBI scores.

Partial MLR and pRDA models using the lake clusters obtained from flexible beta classification could only be conducted for group 1 (northern group, $n = 48$) due to small sample sizes for groups 2 and 3. The fractions of variation for group 1 were not significant when evaluating the pure effects of $\mathbf{A}$ and $\mathbf{E}$ for the both the metric and IBI values. All other fractions of variation were significant ($p < 0.05$, fig. 1.6). The full RDA model using both $\mathbf{A}$ and $\mathbf{E}$ explained 43% of the variance in metric values, whereas the full MLR model explained 42% of the variance in IBI scores. The fractions of variation shared by $\mathbf{A}$ and $\mathbf{E}$ were 26% for the metrics and 19% for the IBI scores. Although the fractions of variation describing the pure effects of $\mathbf{A}$ and $\mathbf{E}$ were not significant for either model, the fractions of variation that separately described the effects of $\mathbf{A}$ and $\mathbf{E}$ without correcting for the shared fractions of variation were significant. Thus, the fractions of variation for the metric values and IBI scores that are shared by $\mathbf{A}$ and $\mathbf{E}$ can be stated with confidence.

1.4 Discussion

1.4.1 The effect of environmental variability on the macrophyte IBI

Our results suggest that a much larger set of explanatory variables than previously considered can explain a significant amount of variation of the response of the macrophyte IBI. Additionally, statewide application of the index without accounting for the effects of environmental variables will be insufficient to identify effects of anthropogenic stressors because a majority of the variation in macrophyte response was shared between anthropogenic and environmental variables (fig. 1.5). Results from clustering and ordination provided information that can be used to develop an appropriate lake classification scheme that minimizes natural variability of the index. As described below, variables significantly correlated with IBI scores and NMS axes could form the basis for defining comparable groups of lakes for bioassessment.

Watershed characteristics, namely soils and geology, exhibited the strongest relationships with IBI scores and explained a substantial amount of variation among study lakes. Geology was chosen as an explanatory variable of IBI response because soil type, which affects chemical and physical characteristics of a lake, is influenced by the content of glacial deposits (Anderson et al., 2001). Therefore, examining watershed geology may not be as important as examining characteristics of the soils to evaluate the effects on macrophyte communities. The soils associated with end moraine and outwash in more northern lakes were more permeable than those associated with stagnation moraine, and also had lower available water content, clay content, and liquid limit. Soil permeability is inversely proportional to contaminant concentration of runoff (Gelbrecht et al., 2005; Shanley et al., 2005), suggesting lakes with watersheds of clay soils receive potentially more nutrient runoff than a lake with a watershed dominated by permeable soils. Additionally, lakes with high amounts of clay in the watershed also had more productive soils (indicated by CPI values), suggesting a more naturally eutrophic baseline than lakes in the central and northern regions of the state.

Several of the watershed and lake variables described landscape position (catchments upstream, lake elevation, watershed area, and watershed elevation range) and explained a significant amount of variation among the lakes. Landscape position can affect the amount of groundwater that enters a lake, which can affect macrophyte communities primarily by altering alkalinity (Kratz et al., 1997; Alexander et al., 2008). All four landscape position variables were positively correlated with the IBI, indicating lakes with lower landscape position had plant communities with higher IBI scores. The relationship of landscape position with IBI scores was especially evident for lakes in the northern cluster. However, the relationship varied by region, such that more southern lakes with lower landscape position generally had lower IBI scores. Interactions of landscape position with region could be explained by land use variability among the state. Land use varies throughout Minnesota such that urban and agricultural land use intensifies towards more southern latitudes. Lakes with larger watersheds (lower landscape position) in southern Minnesota may be more susceptible to water quality degradation through increased nutrient runoff, whereas the opposite may be true in northern Minnesota where forested land is dominant. More detailed assessment of the specific effects of landscape position with IBI performance among regions is needed, particularly regarding interactions with watershed land use.

All of the climate characteristics were strongly correlated with IBI scores and NMS axes, although climate variables were also correlated with latitudinal gradients in land use. For example, lakes with higher annual temperatures and GDD would be expected to have more diverse plant communities (Barko et al., 1982; Rooney and Kalff, 2000), although the opposite trend was observed for our study lakes. Southern macrophyte communities with longer growing seasons (higher mean July temperature and GDD) had lower macrophyte diversity, likely because of potential confounding effects of land use. Conversely, the wind index was not correlated with latitude, but was negatively correlated with IBI scores and positively correlated with NMS axis 1. This suggests that lakes with higher wind action are more likely to have lower IBI scores, regardless of latitude. This observation is significant because most research has evaluated site-level impacts of wind (Chambers, 1987; Riis and Hawes, 2003), whereas the wind index used in our analysis evaluated whole-lake effects. Excessive wind action can mobilize fine sediments and increase turbidity, inhibiting the growth of submersed aquatic plants (Engel and Nichols, 1994). The development of regional assessment frameworks for macrophyte bioassessment should account for the effects of wind in addition to other climate variables.

1.4.2 Macrophyte variability and defining comparable groups of lakes

Perhaps the most important implication from the current study is the difficulty of monitoring aquatic organisms when their response is confounded by anthropogenic and environmental characteristics. The variance partitioning analyses indicated that the index could not differentiate the effects of stressors from natural variability when evaluating the statewide dataset. However, clustering can potentially improve bioassessment by reducing the environmental variability of the index. Our evaluation of the northern lake cluster suggested reduction of environmental variability because the shared variation in the response attributed to anthropogenic and environmental variables decreased relative to the pure effects of both. However, overall model performance was reduced when evaluating the single lake cluster (increased residual variation). This result may be caused by reduced sample size, although clustering could have reduced the range of values for explanatory variables. Similarly, Sass et al. (2010) found that aquatic macrophyte communities in Wisconsin were correlated with land use at the statewide scale but not when grouped by ecoregion.

The use of methods for defining comparable groups of lakes has facilitated efforts for developing biological indices, both internationally (e.g., Moss et al., 2003; Stelzer et al., 2005) and in Minnesota. The macrophyte IBI was developed using lake classes that were identified to manage fishery resources (Schupp, 1992; Beck et al., 2010). Considering the current analysis, the use of a lake classification scheme that was developed primarily for fisheries management may be inappropriate. The spatial distribution of lake clusters in fig. 1.3 suggests that ecoregions (Omernik, 1987) are the most appropriate spatial units for statewide implementation of the macrophyte IBI . From a practical standpoint, the use of a pre-existing classification scheme is a desirable result of the current study. However, the considerable spatial overlap of lake clusters and the grouping of lakes at smaller spatial scales than ecoregions (e.g., four and five clusters) suggests that, from an ecological standpoint, ecoregions do not fully account for the variation in macrophyte communities. This is not surprising since the explanatory variables were selected because of their broad effects on macrophytes, and are not entirely applicable to the criteria used for defining ecoregions. Therefore, an alternative framework may be necessary for defining comparable systems as a basis for statewide implementation of the macrophyte IBI.

Evaluations of alternative lake classification schemes could provide useful information to facilitate the implementation of the macrophyte IBI, in addition to consideration of an ecoregion-approach. For example, Moyle (1945) provided a foundational assessment of the statewide distribution of aquatic plants using water chemistry variables that influence macrophytes. More recent assessments of aquatic plant communities in Minnesota conducted by Reschke et al. (2006) evaluated a much larger dataset ($n = 1984$ lakes) to identify comparable groups. Accordingly, the relationship of environmental characteristics with the macrophyte IBI can be interpreted in the context of studies specific to macrophytes, but also in the context of approaches for defining comparable regions not restricted to aquatic vegetation. For example, Reschke et al. (2006) indicated the need to consider environmental characteristics that exhibit no clear spatial pattern in explaining macrophyte distribution. The spatial distribution of the lake clusters in the current study also supports the groups described in Moyle (1945). Additionally, the macrophyte IBI is strongly influenced by environmental characteristics used to define ecoregions. The identification of comparable groups of lakes to improve use of the macrophyte IBI should consider the utility of different lake classification schemes and the potential implications they may have for developing a more discriminatory index.

Finally, results from our analyses highlight some of the difficulties associated with the use of multimetric indices for bioassessment. IBIs combine information from multiple sources by using metrics that evaluate specific structural or functional components of aquatic ecosystems (Karr et al., 1986). The additive combination of metrics that individually respond to environmental or anthropogenic changes can confound the interpretation of overall IBI scores. For example, our initial variance partitioning analyses illustrated that the index was influenced by both anthropogenic and environmental variables and that considerable variation in index response was shared between the two variable types. Regardless, the rationale for the use of multimetric biological indices is based on the assumption that biological organisms are the most reliable indicators of environmental condition that provide more detailed information than chemical or physical proxies (Karr and Chu, 1999). An additional advantage is the ability of multimetric indices to summarize ecosystem complexity. Single proxy measures (e.g., species richness) do not fully account for the range of biological attributes that respond to environmental degradation and, therefore, may be less effective at identifying and diagnosing causes of biological impairment (Hall and Giddings, 2000). The advantages of multimetric indices have been recognized in the US and internationally (USEPA, 2002; Stelzer et al., 2005; Penning et al., 2008) and the use of quantitative approaches to characterize their performance, such as multivariate methods for lake classification, is necessary for practical implementation.

1.4.3 Conclusions

Use of the macrophyte IBI without considering natural variability in community composition will be unsuccessful in evaluating the specific effects of anthropogenic stressors on lake condition. However, our results provide guidance to facilitate statewide implementation and more general development of macrophyte indices. For example, clustering analyses have indicated that smaller groups of lakes than those considered in the full dataset should be used to identify comparable groups. These lake groups could be defined using the environmental characteristics evaluated in our analyses. Most importantly, once comparable groups of lakes are identified, additional lakes could be surveyed to ensure disturbance gradients are present within each group and adequate reference conditions are identified. Such an approach will enable the creation of alternative scoring criteria for the index that can identify deviation from reference conditions as a basis for evaluating environmental degradation. Successful identification of comparable groups, disturbance gradients, reference conditions, and alternative scoring criteria within each group will likely produce IBIs that have the ability to discriminate differences between signals and noise. These results and suggested approaches for index refinement not only have relevance within Minnesota, but may also be applied in the development of bioassessment methods that have the goal of accurately and precisely determining biological condition.

Table 1.1: Environmental characteristics hypothesized to influence growth patterns and community dynamics of aquatic macrophytes in study lakes. Rows are separated by lake, watershed, and climate variables.

Variable	Description	Mean (Min, Max)
Lake		
depth	maximum depth of lake (m)	10.6 (1.2, 49.7)
lake elevation	lake elevation above sea level (m)	362.8 (207.6, 541.5)
Shoreline Development Index	measure of shoreline complexity (SDI, unitless)	1.8 (1, 3.8)
surface area	lake surface area (km^2)	2.2 (0.2, 16.6)
Watershed		
available water capacity	water capacity of soil (unitless)	0.16 (0.07, 0.26)
catchments upstream	number of catchments upstream of primary lake catchment (count)	7 (0, 81)
clay	clay content of soil (%)	17.3 (4.2, 38.9)
Crop Productivity Index	weighted average of Crop Productivity Index (CPI) for the wshed (unitless)	52.0 (3.7, 91.7)
elevation range	difference in maximum wshed elevation and lake elevation (m)	51.4 (6.4, 167.7)
end moraine	wshed area as end moraine (%)	27.4 (0, 100)
ground moraine	wshed area as ground moraine (%)	14.2 (0, 100)
liquid limit	moisture content of soil required for mobility (%)	29.5 (17.5, 49.6)
organic material	organic material in soil (% moisture by weight)	5.6 (0.8, 21.3)
other geology	wshed area as other geology type (%)	3.3 (0, 90.7)
outwash	wshed area as outwash (%)	29.9 (0, 100)
permeability	permeability of soil (cm/hour)	12 (2, 31)
slope	average slope of wshed (%)	3.4 (0.6, 8.2)
stagnation moraine	wshed area as stagnation moraine (%)	25.2 (0, 100)
thickness	depth of soil layer (cm)	153 (96, 168)
wshed area	wshed surface area (km^2)	127.9 (1.3, 1551)
wshed to surface	ratio of wshed area and lake surface area (unitless)	98.8 (1.2, 1839.6)
Climate		
Growing Degree Days	mean Growing Degree Days (GDD) per year from 1971-2000, 10 °C base (count)	2337 (1547, 2763)
July temp	average July air temperature for lake (°C)	21.1 (18.3, 22.8)
wind index	wind index accounting for fetch, wind power, and direction (unitless, in thousands)	58 (10, 165)
wshed precip	mean annual precipitation in the wshed from 1971-2000 (cm)	72 (61, 83)

Table 1.2: Anthropogenic characteristics of study lakes used in variance partitioning analyses to identify the relative influence of stressors on IBI and metric values.

Variable	Description	Mean (Min, Max)
agriculture	relative amount of wshed land use as agriculture (%)	29.8 (0, 86.8)
urban	relative amount of wshed land use as urban (%)	9.6 (0.7, 62.1)
forest	relative amount of wshed land cover as forest (%)	36.8 (0.6, 88.9)
trophic state index	proxy of cultural eutrophication (TSI, unitless)	55.7 (31.9, 93.1)

Table 1.3: Spearman rank correlations of environmental characteristics with nonmetric multidimensional scaling axes. See table 1.1 for description of variables. Rows are separated by lake, watershed, and climate variables. * indicates $p < 0.05$ and ** indicates $p < 0.005$.

Variables	NMS1	NMS2	NMS3
Lake			
depth	-0.29**	0.23*	0.55**
lake elevation	-0.4**	-0.24*	0.18
Shoreline Development Index	-0.2*	-0.21*	0.39**
surface area	-0.06	-0.38**	0.27*
Watershed			
available water capacity	0.62**	0.2	0.49**
catchments upstream	-0.28**	-0.85**	0.34**
clay	0.86**	-0.01	0.32**
Crop Productivity Index	0.83**	-0.01	-0.1
elevation range	-0.37**	-0.3**	0.45**
end moraine	-0.47**	0.4**	0.47**
ground moraine	0.24*	-0.29**	-0.11
liquid limit	0.82**	-0.03	0.3**
organic material	-0.25*	0.2	0.31**
other geology	0.03	-0.17	0.03
outwash	-0.69**	-0.28*	-0.37**
permeability	-0.83**	-0.06	-0.27*
slope	-0.25*	0.42**	0.49**
stagnation moraine	0.7**	-0.16	0.15
thickness	0.02	0.02	0.43**
wshed area	-0.2	-0.78**	0.33**
wshed to surface	-0.14	-0.55**	0.17
Climate			
Growing Degree Days	0.73**	0.12	-0.23*
July temp	0.69**	0.15	-0.33**
wind index	0.4**	-0.36**	-0.01
wshed precip	0.28**	0.41**	0.12

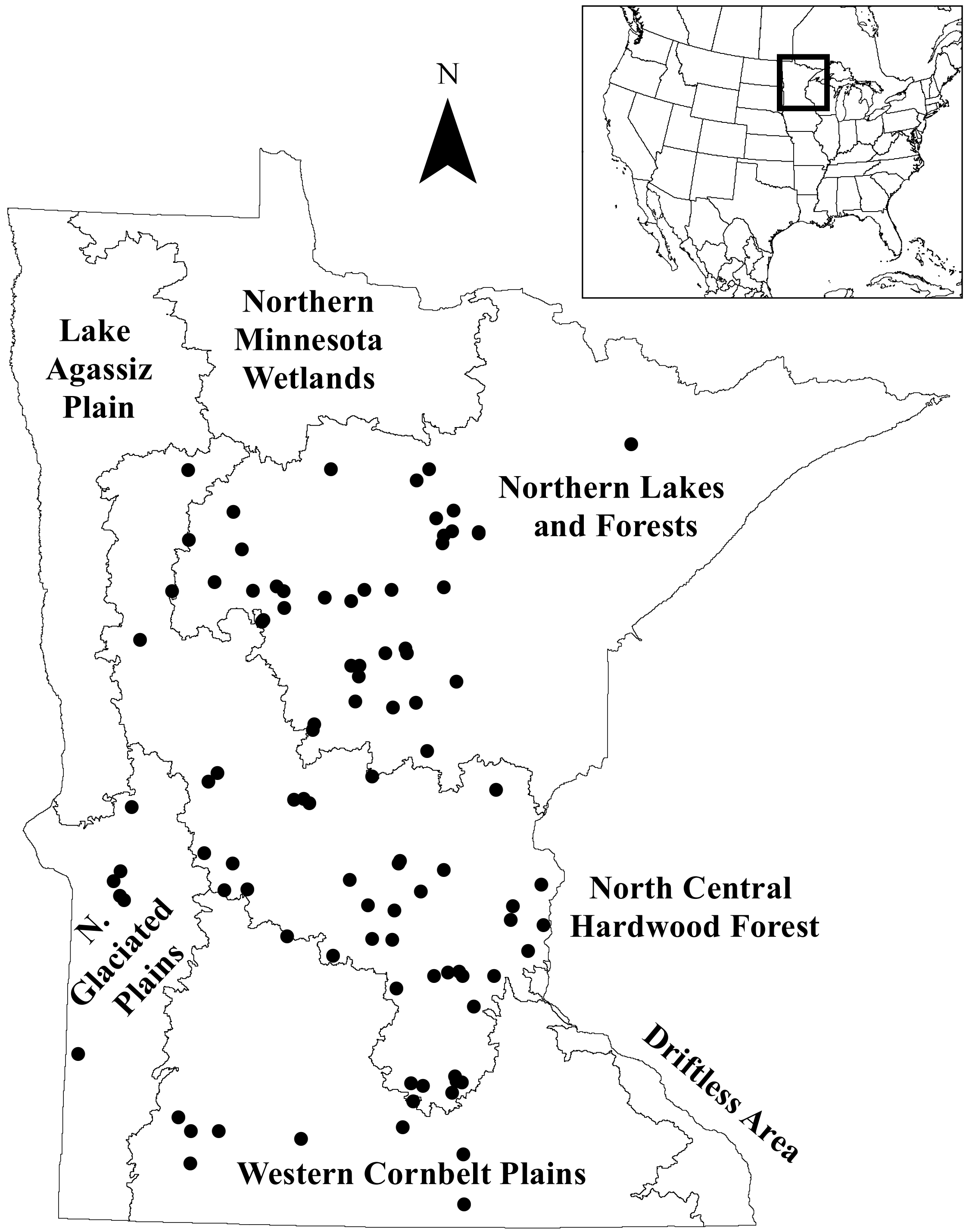


Figure 1.1: Ninety-seven lakes used to evaluate performance of the macrophyte-based index of biotic integrity (Beck et al., 2010). Boundaries indicate ecoregions described in Omernik (1987).

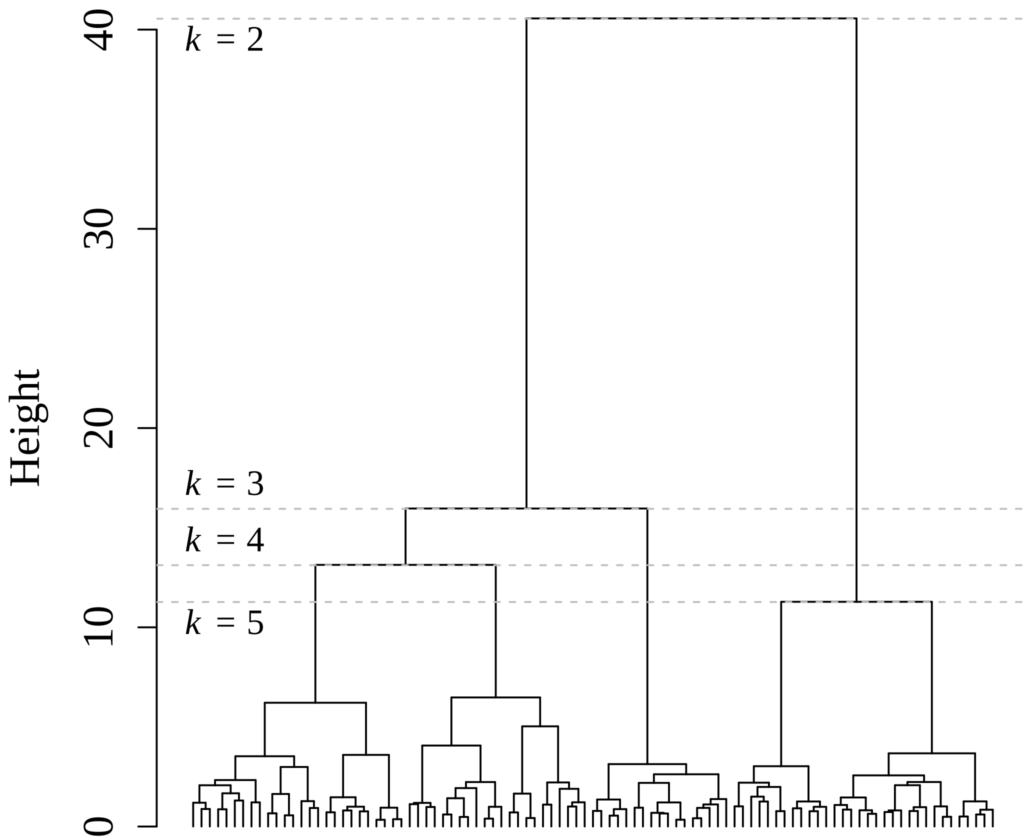


Figure 1.2: Lake clusters based on environmental characteristics. Clusters were obtained using flexible beta classification and β = -0.5 as the sorting parameter. Two through five groups (k) were obtained by cutting the classification dendrogram at various heights. Lakes within groups separated at lower height values are more similar.

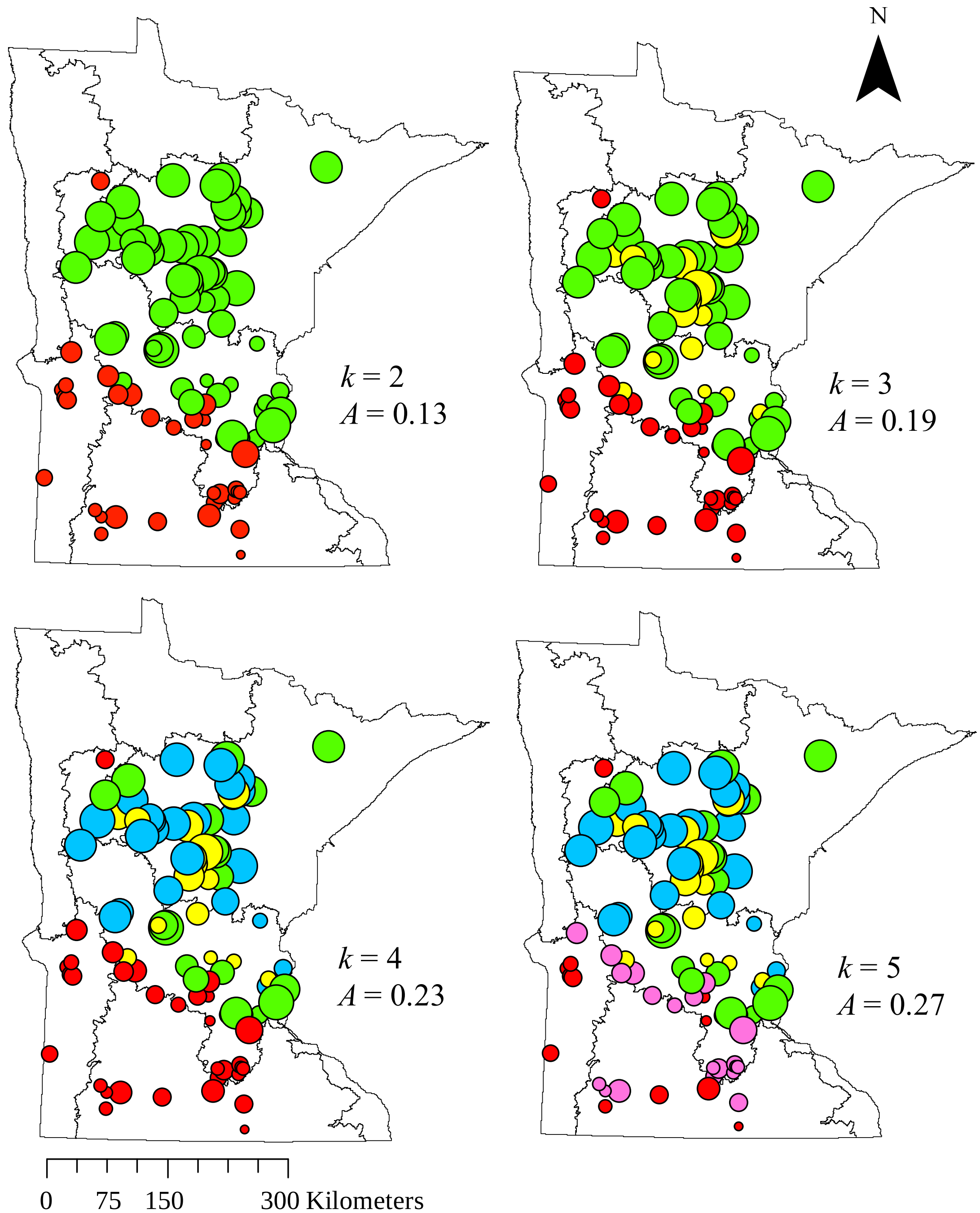


Figure 1.3: Spatial arrangement of lake groups (k) obtained from flexible beta classification using environmental variables that influence macrophyte community composition. Colors represent the lake clusters obtained from cutting the dendrogram in fig. 1.2 at different heights. 'A' is the effect-size determined from multiple-response permutation procedures and describes similarity within groups (0 = random, 1 = identical). Size of each lake point is proportional to IBI score. Boundaries indicate ecoregions described in Omernik (1987).

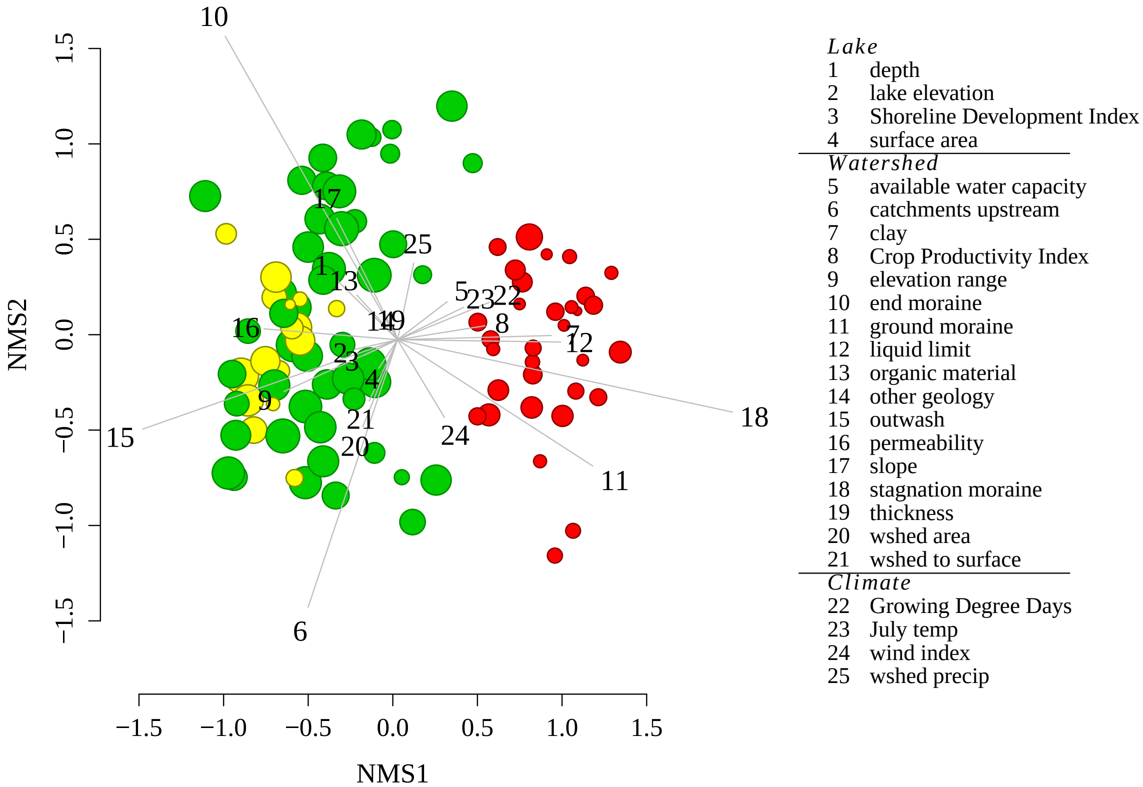


Figure 1.4: Ordination results obtained from nonmetric multidimensional scaling for axes 1 (NMS1) and 2 (NMS2). Orientation and length of vectors originating from the origin indicate the sign and magnitude of the correlation for each environmental variable with each axis. Data points are color-coded by group as in fig. 1.3 (top-right, $k = 3$) and size is proportional to IBI score. See table 1.1 for description of variables (grouped by lake, watershed, and climate characteristics) and fig. A.3 for plots of additional NMS axes.

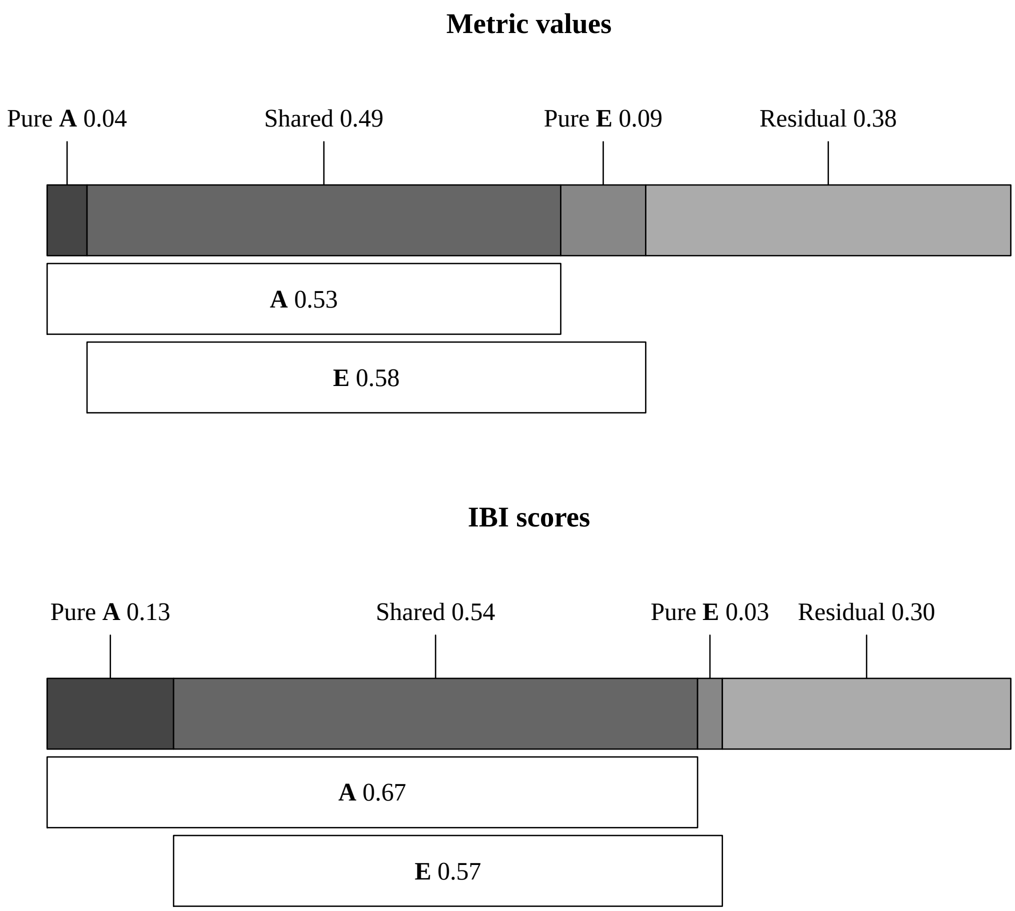


Figure 1.5: Variance partitioning of metric values and IBI scores among anthropogenic (**A**) and environmental (**E**) variables for 97 lakes. Metric variation was determined using partial redundancy analysis and IBI variation was determined using partial regression analysis. Adjusted fractions of variation were used.

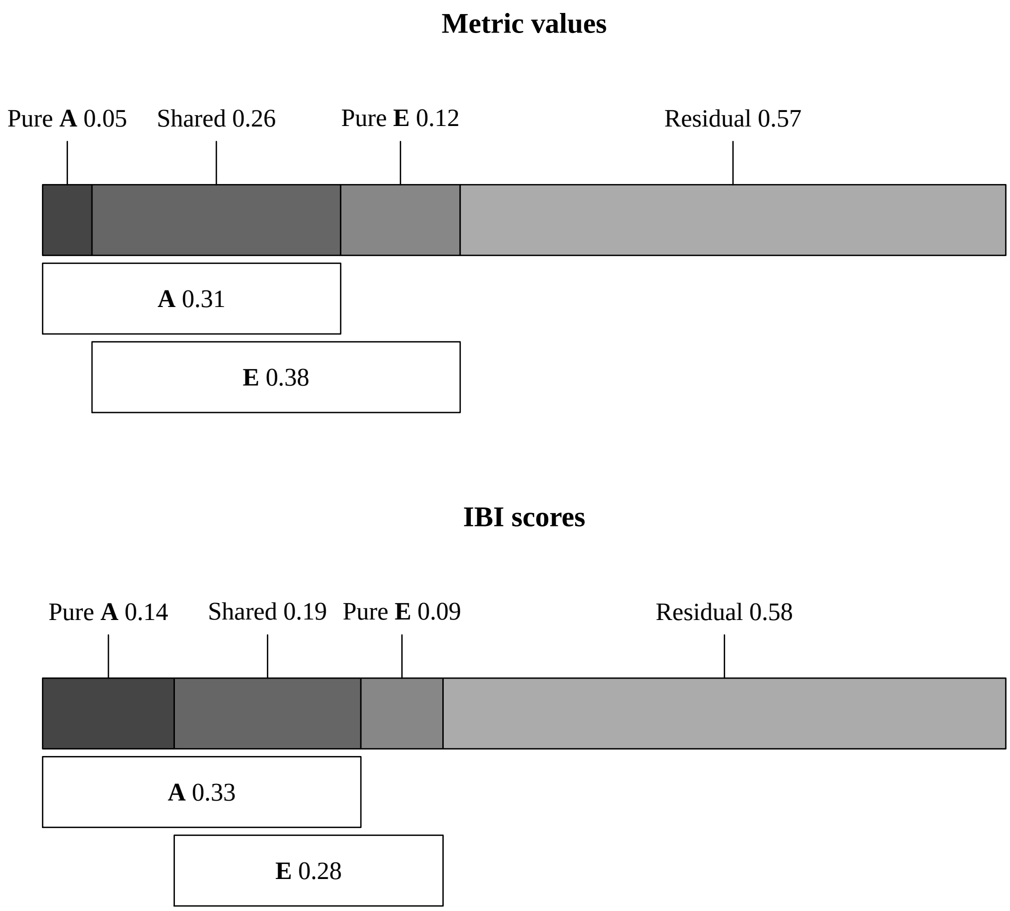


Figure 1.6: Variance partitioning of metric values and IBI scores among anthropogenic ($\mathbf{A}$) and environmental ($\mathbf{E}$) variables for a single cluster ($n = 48$, northern group for $k = 3$ in fig. 1.3) of the entire dataset ($n = 97$). Metric variation was determined using partial redundancy analysis and IBI variation was determined using partial regression analysis. Adjusted fractions of variation were used.

Chapter 2

Semi-automated analysis of high-resolution aerial images to quantify docks in glacial lakes

Abstract

Lake resources can be negatively affected by environmental stressors originating from multiple sources and different spatial scales. Shoreline development, in particular, can negatively affect lake resources through decline in habitat quality, physical disturbance, and impacts on fisheries. The development of remote sensing techniques that efficiently characterize shoreline development in a regional context could greatly improve management approaches for protecting and restoring lake resources. The goal of this study was to develop an approach using high-resolution aerial photographs to quantify and assess docks as indicators of shoreline development. First, we describe a dock analysis workflow that can be used to quantify the spatial extent of docks using aerial images. Our approach incorporates pixel-based classifiers with object-based techniques to effectively analyze high-resolution digital imagery. Second, we apply the analysis workflow to quantify docks for 4,261 lakes managed by the Minnesota Department of Natural Resources. Overall accuracy of the analysis results was 98.4% (87.7% based on $\hat{K}$) after manual post-processing. The analysis workflow was also 74% more efficient than the time required for manual digitization of docks. These analyses have immediate relevance for resource planning in Minnesota, whereas the dock analysis workflow could be used to quantify shoreline development in other regions with comparable imagery. These data can also be used to better understand the effects of shoreline development on aquatic resources and to evaluate the effects of shoreline development relative to other stressors.

2.1 Introduction

The increasing presence of permanent or seasonal homes on lake shorelines has been a cause for concern among lake managers given the potential impacts of human activities associated with these properties. Home-owners can alter shoreline characteristics by preferential removal of aquatic vegetation or through the addition of unnatural structure (e.g, docks, rip-rap). The potential effects of shoreline development may contribute to declines in habitat quality (Christensen et al., 1996; Radomski and Goeman, 2001; Jennings et al., 2003; Marburg et al., 2006; Radomski, 2006), having associated effects on fish spawning success and population structure (Jennings et al., 1999; Garrison et al., 2005; Wagner et al., 2006; Reed and Pereira, 2009; Gaeta et al., 2011). Although the potential effects of shoreline development have been recognized, the precise implications for the protection of lake resources are unclear in the context of whole-lake management. For example, the relative effects of both shoreline development and watershed-based stressors are unclear considering potential interactions among factors that influence water quality. Additionally, researchers have not extensively evaluated the cumulative effects of shoreline development on whole-lake condition relative to site-level impacts (but see Jennings et al., 1999; Marburg et al., 2006). Lack of quantitative information describing shoreline development across broad areas has been a primary research limitation.

The use of Geographical Information System (GIS) and remote sensing technologies to quantify environmental stressors of lakes has importance given the potential to accurately quantify information across multiple spatial scales. Several techniques using GIS or remote sensing approaches have been proposed for evaluating lake resources in the Upper Midwest United States (Sawaya et al., 2003; Host et al., 2005; Olmanson et al., 2008; Chipman et al., 2009; Olmanson et al., 2011). Olmanson et al. (2008) developed an approach for evaluating water clarity using imagery from the Landsat satellite. Water clarity for more than 10,500 lakes in Minnesota was determined by developing linear regression models of *in situ* measurements of water clarity compared with surface radiance values obtained from Landsat imagery. Additionally, Sawaya et al. (2003) described the development and application of remote sensing techniques to quantify information relevant for lake management at the local scale. The application of GIS and remote sensing technologies for the management of aquatic resources has shown promise and should be further investigated to determine whether additional techniques can be developed.

Most remote sensing techniques for lake management have primarily focused on assessing lake condition prior to the implementation of management actions (e.g., Host et al., 2005; Olmanson et al., 2008) but have not focused on the explicit quantification of relevant stressors. More importantly, available data that can be used to quantify stressors, such as satellite-derived land use information, have inadequate spatial resolution to characterize shoreline development. Specifically, Landsat-derived products describe land use in 30m grid cells that cover 900 m^2, whereas most docks typically do not exceed 15-20 m^2 (MNDNR, 2011). In the absence of sufficient or appropriate data, researchers are limited to manual techniques or *in situ* assessments for quantifying information (e.g., Radomski et al., 2010; Perleberg et al., 2012), although these techniques cannot be practically applied to regional evaluations. Additionally, efforts to quantify stressors of aquatic systems must consider appropriate surrogate measures (Danz et al., 2007; Wang et al., 2010), such as indicators for multiple shoreline-based stressors. Docks are potentially useful indicators because they can directly impact habitat (Garrison et al., 2005; Radomski et al., 2010) and are indirectly associated with other stressors (Jennings et al., 2003; Radomski, 2006), such as recreational activity at the site-level, or housing density at the whole-lake spatial scale. Ease of identification in aerial imagery further supports their use as a surrogate measure (Radomski et al., 2010).

Image classification techniques for quantifying shoreline development have not been extensively developed despite the increasing availability of high-resolution (1 m or better) digital imagery. Traditional approaches for image classification have relied on pixel-based techniques where individual pixels are assigned to classes defined by clustering (Richards and Jia, 2006a,b; Homer et al., 2007; Jensen et al., 2009). Ideally, classes should correspond to thematic categories of interest in the image, such as land use or cover. Pixel-based classifiers can be used with high-resolution imagery but problems are encountered when the pixel size is significantly smaller than the classes of interest. Multiple pixels with different spectral properties may describe a single object or the dependence among neighboring pixels may introduce bias in the classification (Townshend et al., 2000; Blaschke and Strobl, 2001). Object-based image analysis has been proposed as an alternative approach that seeks to identify objects defined by groups of pixels with similar spectral and spatial characteristics (Hay and Castilla, 2008; Lang, 2008; Blaschke, 2010). Image objects (i.e., vector polygons) define the fundamental units of interest for identifying real-world objects. Object-based image analysis applied with more traditional methods of image classification could provide a powerful approach for quantifying stressors in nearshore environments.

The goal of this study was to develop a cost-effective approach for quantifying and assessing the extent of shoreline development of glacial lakes in the Upper Midwest United States. First, we describe a dock analysis workflow that can be used to quantify docks using high-resolution digital imagery. This workflow combines elements of traditional pixel-based classifiers with object-based approaches to create a semi-automated analysis for enumerating docks and estimating dock area. We focused on the development of techniques that can be applied across broad regions rather than methods with limited spatial scope. Accordingly, our second objective was to use the workflow to quantify the extent of shoreline development in Minnesota using images for 4,261 lakes that are managed by the Minnesota Department of Natural Resources (MNDNR). These results have immediate relevance for MNDNR planning, whereas the dock analysis workflow could easily be extended to other states or regions with comparable imagery. This study also considers docks to be adequate indicators of a majority of stressors that result from shoreline development (Garrison et al., 2005; Radomski et al., 2010). Here and throughout, 'docks' refer to docks, boat lifts, trampolines, fishing piers, and other structures on the water that do not naturally occur in nearshore environments.

2.2 Material and Methods

2.2.1 Data and software

Digital aerial images from the 2008 National Agricultural Imagery Program (NAIP) were used for the development and application of our dock analysis workflow described below. NAIP images are leaf-on images (May through September) with 1 m resolution and are available annually for the entire United States (USDA, 2011). The 2008 images also contain a near infrared (NIR) spectral band, in addition to the standard red, green, and blue spectral bands, which was useful for removing vegetation from images and improving identification of relevant classes during analysis. Each pixel in each band has an 8-bit digital number (DN) value as a measure of surface radiance ranging from 0 to 255. NAIP images were obtained as ortho-rectified county mosaics for eighty-four of Minnesota's eighty-seven counties that contained our study lakes. Image acquisition dates varied such that 12% were in May, 9% were in June, 28% were in July, 47% were in August, and 4% were in September. The county mosaics were obtained in the JPEG 2000 (.jp2) format and included 87.8 gigabytes of data.

The workflow was implemented using the ArcGIS v9.3 (Esri, 2009) geo-processing object in the programming language Python v2.6.5

(http://www.python.org/, listings B.1 and B.2). The use of Python to write scripts specific for ArcGIS improved efficiency of the analysis by combining all components of the workflow in a single script file. Similar utilities are not readily available using other image analysis software. Potential users of the dock analysis workflow are also more likely to have access to ArcGIS rather than more specific image analysis software.

2.2.2 Description of the dock analysis workflow

The dock analysis workflow consists of three separate processes: 1) shoreline correction; 2) dock extraction; and 3) manual post-processing (figs. 2.1 and 2.2). Individual images bounded by the minimum and maximum Universe Transverse Mercator coordinates for each lake are used as input for the analysis workflow. The following describes each process of the workflow in more detail.

The dock analysis workflow begins with the *shoreline correction process* (figs. 2.1 and 2.2 and listing B.1). The goal of this process is to create an accurate lake polygon that can be used to clip the input image in the beginning of the dock extraction process. Available lake polygons ('DNR 100k Lakes and Rivers' shapefile, MNDNR, 2012a) were insufficient for this task due to inconsistencies between the polygon boundaries and the actual shoreline in the image. Several steps are used for shoreline correction. First, the original lake polygon is buffered by 50 meters and used as a mask to clip relevant portions of the image. Second, the clipped lake image is then classified using an unsupervised, pixel-based classification technique available in ArcToolbox ('IsoCluster' and 'MLClassify' tools, Cleve et al. 2008; Jensen et al. 2009). Third, an algorithm is used to select classes with spectral properties that are characteristic of water, particularly those with low DN values relative to other classes. The final set of classes are merged and converted to vector format. The merged lake polygon is buffered by 5 meters and buffered again by -5 meters to create a continuous lake polygon without holes.

The second process of the dock analysis workflow is the *dock extraction process* (figs. 2.1 and 2.2 and listing B.2). The corrected polygon from the shoreline correction process and the original lake image are used as input. The corrected lake polygon is buffered by -70 meters and used to clip the lake image because docks were not observed beyond 70 meters from the shore. The clipped image is then classified using pixel-based classification techniques. Classes corresponding to docks are identified using an algorithm that selects classes with high DN values for each spectral band. Therefore, the approach distinguishes potential dock classes from the surrounding water based on the relative differences in the DN values among the classes identified by the classification tools in ArcGIS. Additional algorithms are used to remove classes that described other 'bright' features that were not docks. For example, vegetation could be removed by identifying classes with high values for the NIR band.

The dock extraction process also incorporates object-based image analysis techniques. Lake images are segmented using an edge-based segmentation algorithm available in ERDAS Imagine 2010 (ERDAS, 2010). Image segmentation combines pixels into homogeneous regions (i.e., vector polygons) based on user-defined parameters (Blaschke and Strobl, 2001; Schöpfer et al., 2008). The edge-based segmentation algorithm implemented in ERDAS Imagine 2010 creates objects by edge identification and additional criteria, such as differences and variances of pixel values within objects and sizes of objects (table 2.1, Schöpfer et al. 2008). Segmentation is completed prior to implementation of the dock extraction process and is the only component of the workflow that requires additional software. A size filter is used on the segmented image to remove objects > 200 m^2. The temporary dock layer created from pixel-based classification is then clipped using the segmented image. The remaining polygons in the clipped image are filtered using additional size and spectral criteria to further identify docks.

The third and final process of the dock analysis workflow is *manual* *post-processing* to improve accuracy (figs. 2.1 and 2.2). Initial assessments of the analysis output indicated that approximately half of the polygons were not docks (low commission accuracy), although almost all of the docks in the images were included (high omission accuracy). All polygons are visually identified using photo-interpretation of the original images. Polygons that are not docks (hereafter referred to as 'erroneous' polygons) are removed.

2.2.3 Implementation of the dock analysis workflow

Our second objective was to illustrate the utility of the dock analysis workflow by quantifying the extent of shoreline development in Minnesota. The outcome of this objective was the identification of areas that could be prioritized for management as a result of the potential impacts of shoreline development. A total of 4,261 lakes managed by the MNDNR were assessed using the dock analysis workflow. Post-processed dock data for these lakes were summarized as dock counts, dock density (docks per shoreline km), dock area (m^2), and dock area scaled by lake area (%). Dock density was also summarized by ecoregion (level III described in Omernik 1987, with the addition of level IV Border Lakes ecoregion), county, and sub-basin (major watershed, Hydrologic Unit Code or HUC level eight). The processing time for all lakes and average processing time for an individual lake was determined for each process of the dock analysis workflow (shoreline correction, dock extraction, and post-processing). We compared processing times for manual post-processing of individual lakes to those required for manual digitization of docks on a set of lakes independently evaluated by Radomski et al. (2010).

Accuracy of the analysis results was determined before and after post-processing using reference data created from photo-interpretation of the aerial images. A stratified random sampling design was used to create points in the classified dock polygons and areas of the images that were not included in the polygons. One hundred points were created in the dock polygons and 400 points were created outside of the polygons. Each point was then visually compared with the reference data to determine overall accuracy, user's accuracy (errors of commission) and producer's accuracy (errors of omission) for the dock classification (Congalton, 1991). Lastly, a KHAT ($\hat{K}$) statistic was calculated as an estimate of Kappa to provide an additional measure of overall classification accuracy (Cohen, 1960; Congalton, 1991). $\hat{K}$ can provide a more robust interpretation of overall accuracy if user's or producer's accuracy is low for a given classification (Congalton, 1991).

We also conducted accuracy assessments to determine accuracy on a per-lake basis. Simple linear regression models ($\log + 1$ transformed data, $\alpha = 0.05$) were used to compare the 'true' number and area of docks to the classified number and area of docks, both before and after post-processing. Manually digitized dock polygons for a set of 101 lakes described in Radomski et al. (2010) were considered a 'true' estimate of dock counts and dock area. Regression models with slope values approximately equal to one indicated that the classified number or area of docks provided an accurate estimate of true count or area data. Conversely, slope values significantly less than one indicated consistent over-estimation of true dock data and slope values significantly greater than one indicated consistent under-estimation of true dock data by the analysis workflow.

2.3 Results and Discussion

2.3.1 Processing

Total processing time using the workflow to analyze 4,261 lake images was approximately 578 hours allocated among the automated processes (shoreline correction and dock extraction) and manual post-processing. Mean total processing time for a single lake was eight minutes and 23 seconds. Shoreline correction required 252 hours of processing with a mean of three minutes and 32 seconds per lake. Dock extraction required 207 hours of processing time with a mean of two minutes and 54 seconds per lake. Manual post-processing removed 129,551 erroneous polygons and required 118 hours with a mean of one minute and 57 seconds per lake. Erroneous polygons were most often emergent vegetation, sun glare, beaches, or other shoreline objects with high radiance. Average processing time per lake for manual digitization of docks conducted by Radomski et al. (2010) was seven minutes and 37 seconds (L. Bergquist, MNDNR, personal communication), which indicates that the time required for manual post-processing using our methods is 74% more efficient.

The first objective was to describe a dock analysis workflow that can be used to accurately and efficiently quantify docks. This workflow combined the use of pixel-based classifiers with object-based techniques to sufficiently accommodate the challenges of analyzing high resolution imagery. For example, docks were often characterized by multiple pixels that could not be defined by a single class. The application of pixel-based classifiers to categorize docks required multiple classes to be used in the classification, which were then identified and combined for further analysis. Similarly, object-based approaches evaluated the characteristics of each polygon (i.e., size and spectral filters in the dock extraction process). Segmented images created by edge detection were particularly effective at identifying docks with clearly defined boundaries (table 2.1, ERDAS, 2010). The use of alternative segmentation techniques, such as the popular Fractal Net Evolution Approach (Baatz and Schäpe, 2000; Schöpfer et al., 2008), was not evaluated but may improve overall accuracy and reduce post-processing time. The size and spectral filters independent of the segmentation process were meant to approximate some of the utilities provided by the Fractal Net Evolution Approach, such as the ability to create image objects based on minimum criteria for size, shape, and color. The automated object-based techniques effectively removed 6,824,606 polygons, a vast majority of which did not characterize objects of interest. In comparison, manual post-processing removed 1.9% of erroneous polygons.

We were also interested in evaluating the spectral characteristics of polygons before and after post-processing to determine if additional information could be identified as a means to improve classification accuracy. The average spectral values for the red, green, blue, and NIR spectral bands within each polygon were quantified. Average values varied for polygons identified as docks or erroneous during post-processing (fig. 2.3). Mean values for the red, green, and blue spectral bands were significantly higher for dock polygons as compared to erroneous polygons (red: t = 300.7, df = 230,045, $p < 0.005$, green: t = 262.6, df = 213,437, $p < 0.005$, blue: t = 191.2, df = 218,003, $p < 0.005$), whereas mean values for the NIR spectral band were significantly lower (t = -42.8, df = 233,586, $p < 0.005$). Of particular interest is the difference in the mean values for the red spectral band relative to the other spectral bands, such that the mean values were 193 for docks and 170 for erroneous polygons. An additional spectral filter could be used to discriminate docks from erroneous polygons given the relative difference in the red spectral band between these polygon types.

2.3.2 Accuracy assessment

Accuracy estimates for all lakes varied before and after post-processing (table 2.2). Overall accuracy of the data before post-processing was 85.6% and 40.8% from the $\hat{K}$ statistic. User's and producer's accuracy for docks were 32.0% and 88.9%. High producer's accuracy indicated that the automated processes were effective at including a majority of docks in the image. However, low user's accuracy indicated that many of the polygons included in the results were not docks. Overall accuracy of the data after post-processing was 98.4% and 87.7% from the $\hat{K}$ statistic. User's and producer's accuracy for docks were 83.8% and 93.9%, indicating a large improvement in user's accuracy after post-processing. The individual lake comparison of 'true' dock data with data from the image analysis techniques indicated that actual dock count and area could be accurately determined using the dock analysis workflow (fig. 2.4). Specifically, coefficients of determination (R^2) for each regression model indicated that a majority of the variance of the 'true' dock area could be explained by data from the image analysis techniques. However, all regression models had slope values significantly less than one ($p < 0.005$ for all).

Our comparison of dock counts and dock area to the independent estimates from Radomski et al. (2010) provided a complementary approach to the point-based estimates of accuracy by evaluating individual polygons for a number of lakes (Castilla and Hay, 2008; Lang, 2008). These assessments indicated reasonable estimates of actual dock counts and area could be obtained, although our results provided minor but systematic over-estimation of dock counts and area (i.e., slope less than one). Dock counts could be over-estimated if individual docks were characterized by more than one polygon. Additionally, area estimates may be inflated if boundaries between docks and beaches were indistinguishable, which often contributed to the creation of large polygons that included both beaches and docks. In this context, beaches refer to cleared portions of lake shorelines that are often associated with docks. Although polygons for beaches were removed in post-processing, polygons were retained if they included any portion of a dock. Inter-annual variability in dock placement could also have caused differences in the results because Radomski et al. (2010) used images from 2003 and 2004, whereas we used images from 2008. Furthermore, NAIP images are obtained from a range of dates throughout the summer (section 2.2.1) and many lakeshore home-owners do not keep docks on the water throughout the year. Comparison of images obtained earlier in the summer with those obtained later in the summer may create discrepancies in estimates of shoreline development because many docks may not be on the water until later in the summer season. Docks may also be more difficult to identify in images acquired later in the growing season due to a higher abundance of emergent vegetation.

2.3.3 Evaluation of shoreline development in Minnesota

Our second objective was to evaluate statewide trends in dock densities. Shoreline development varied such that some lakes had no development (zero docks), whereas others were extensively developed (ranging from one to 3,641 docks, table 2.3 and fig. B.1). Of the 4,261 lakes that were processed, 1,930 lakes did not have docks. Summary data for all lakes are indicated in table 2.3. The top five lakes for dock count, density, area, and area scaled are shown in table 2.4.

Summaries of dock density by ecoregion indicated that dock development was not evenly distributed among ecoregions in Minnesota (fig. 2.5a). Mean dock density was highest in ecoregions in central Minnesota, specifically in the North Central Hardwood Forests (4.1 docks/km) and Northern Lakes and Forests (2.7 docks/km) ecoregions. Other ecoregions had significantly lower mean dock density, specifically those in north-eastern (Border Lakes ecoregion) and north-western (Red River Valley ecoregion) Minnesota. The Border Lakes ecoregion had the lowest mean dock density (0.1 docks/km). Ecoregions in southern Minnesota had either low (Northern Glaciated Plains ecoregion) or moderate (Western Cornbelt Plains ecoregion) dock density. Distribution of dock density categories by ecoregion (fig. 2.5b) were similar to trends in mean dock density. For example, ecoregions with high mean dock density had a higher percentage of lakes in the higher development categories and ecoregions with low mean dock density had a higher percentage of lakes in lower development categories. Summaries of dock density by county (fig. 2.6) and sub-basins (fig. 2.7) produced comparable results. Counties and sub-basins in the central part of the state and near the Twin Cities metropolitan area had the highest mean dock densities. The top five counties and top five sub-basins are described in table 2.5.

Summaries of dock densities by ecoregions, counties, and sub-basins suggest that shoreline development is correlated with high population densities or lakes that support multiple resources. For example, Moyle (1956) described statewide trends in lake trophic state and fish community variability such that lakes in central Minnesota have moderate to low trophic status (i.e., good water clarity) and support productive, coolwater fisheries (Moyle, 1956; Heiskary and Wilson, 2008). Therefore, the limnological characteristics of lakes in the North Central Hardwood Forests and Northern Lakes and Forests ecoregions make them desirable for shoreline property ownership (Krysel et al., 2003). Population growth rates have also been highest in these two ecoregions compared to other areas of the state. For example, Sherburne county (second highest mean dock density) in the North Central Hardwood Forests ecoregion experienced a population increase of 42% from 1990 to 1998 (EQB, 2000).

The absence of excessive shoreline development in other areas (e.g., Border Lakes, Northern Glaciated Plains, Red River Valley ecoregions) also reflects trends in population growth and predominant limnological characteristics. For example, the Border Lakes ecoregion contains an abundance of lakes comparable to central and north-central areas of Minnesota, yet many of these lakes have very little or no shoreline development. Recent population growth observed in central and north-central Minnesota have not occurred in the Border Lakes ecoregion (an exception being areas of St. Louis county near Duluth, EQB, 2000). Additionally, many lakes in the Border Lakes ecoregion are within protected areas, such as Voyageurs National Park, the Boundary Waters Canoe Area Wilderness, and numerous state parks. Other ecoregions may lack extensive shoreline development because of less desirable limnological characteristics (Krysel et al., 2003; Dodds et al., 2009). For example, lakes in the Northern Glaciated Plains ecoregion in southern Minnesota are predominantly shallow, exhibit poor water clarity, and are dominated by fish communities that are less desirable for anglers. Consequently, demand for shoreline property in this ecoregion may be substantially lower than other areas of the state with higher dock densities.

2.3.4 Comparison with alternative methods

A majority of studies focusing on nearshore development have evaluated potential effects rather than developing methods for quantifying stressors. Studies have primarily focused on evaluating the effects of shoreline development on aquatic habitat (Christensen et al., 1996; Radomski and Goeman, 2001; Jennings et al., 2003; Radomski, 2006) and associated impacts on fish populations (Jennings et al., 1999; Schindler et al., 2000; Scheuerell and Schindler, 2004; Wagner et al., 2006; Reed and Pereira, 2009; Gaeta et al., 2011). These studies have generally focused on pre-selected lakes that fit a given criteria based on particular questions and objectives. Although such approaches are useful for evaluating specific questions, comparisons among studies becomes challenging when different groups of lakes in a particular area are evaluated. Our results were compiled for 4,261 lakes that were selected based only on the criteria that they are managed by MNDNR. Although we have not used our data to evaluate potential effects of shoreline development, the quantification of nearshore data for such a large data set will allow researchers to more easily compare information among lakes with different limnological characteristics and across broad spatial areas.

Very few studies have focused on the sole development of techniques for quantifying lake stressors in nearshore environments. One exception is the analysis conducted by Radomski et al. (2010), although the focus was not method development. In their study, docks were also assumed to be adequate indicators of nearshore stressors and were quantified for a group of 174 lakes in north-central Minnesota. Their results suggested that docks impacted 14% of shorelines and 3% of littoral zones, whereas under hypothetical development scenarios docks were expected to impact up to 50% of lake shorelines and 14% of littoral zones. Although largely based on assumptions of dock impacts, their study represents a significant contribution to our understanding of the extent and magnitude of shoreline development in glacial lakes. A logical extension of our results would be the application of similar methods to characterize hypothetical impact zones and projected development scenarios for our larger set of 4,261 lakes.

The development of remote sensing and GIS techniques to facilitate the management of aquatic resources has been the focus of multiple studies relevant for the Upper Midwest (Host et al., 2005; Olmanson et al., 2008; Chipman et al., 2009; Olmanson et al., 2011). To the best of our knowledge, no studies have focused on the explicit quantification of docks or other structures using automated or semi-automated approaches. Comparable studies using high-resolution imagery have focused only on water clarity or aquatic vegetation mapping. Sawaya et al. (2003) developed an approach for characterizing lake water clarity and aquatic vegetation types (by growth form) using high-resolution imagery obtained from the IKONOS and QuickBird satellite platforms. Additionally, impervious surfaces were also mapped in lake watersheds to quantify stressors that negatively affect water clarity. Their approach relied heavily on standard image classification techniques in addition to manual image processing to improve classification accuracy. Although adequate results were obtained, the methods were applied to a limited spatial area and have not been extensively evaluated in a regional context. Radomski and Goeman (2001) and Radomski (2006) also described an image classification approach for quantifying the spatial extent of aquatic vegetation in Minnesota lakes using a clustering technique similar to our analysis. Their approach appeared to have merit for achieving study objectives, although the development of image classification techniques was not a primary focus.

2.4 Conclusions

The dock analysis workflow increases efficiency of data acquisition by 74% and represents a substantial improvement over manual techniques for quantifying nearshore stressors. More importantly, we have developed a method that can use imagery obtained on multiple acquisition dates. Therefore, the dock analysis workflow can effectively analyze data with different spectral characteristics and application of the workflow to other regions should require minimal effort, provided resources are available for post-processing and input data are available. Additional development of these techniques could also improve accuracy and further reduce post-processing time. For example, the use of high-resolution imagery with sub-meter resolution, incorporation of additional object filters, or the adaptation of the workflow to incorporate Light Detection and Ranging (LIDAR) data could greatly improve accuracy of the results. Use of LIDAR data, although computationally intensive, could improve edge detection of docks.

Application of the dock analysis workflow to quantify the spatial extent of shoreline development in Minnesota has highlighted particular areas of the state with lakes that could be at risk of resource degradation. Specifically, lakes in the North Central Hardwood Forests and Northern Lakes and Forests ecoregions have dock densities much higher than other ecoregions, with many lakes in the highest dock development category (fig. 2.5b). The abundance and diversity of lake resources in these ecoregions, in addition to trends in population growth and property ownership, likely explain the high dock densities. Regardless of potential mechanisms that explain trends in shoreline development, lakes that exhibit high dock densities could be at risk of resource degradation and could be managed accordingly. Current regulations that govern activities related to shoreline development in Minnesota may be inadequate to protect lake resources. Shoreline property owners are currently allowed to remove submerged vegetation in areas less than 232 m^2 (2,500 ft^2) or along a 15 m (50 ft) length of shoreline (MNDNR, 2012b). These regulations were established using a precautionary principle to ensure that no more than 50% of a lake's shoreline is affected by mechanical harvesting of vegetation (Valley et al., 2004; Radomski et al., 2010), yet this threshold has not been empirically validated nor does it consider direct impacts of docks (Garrison et al., 2005). Regulatory agencies may be limited to prevention and education as primary tools to mitigate the effects of resource degradation. The data from our analysis will provide valuable information that can be used to further support efforts at protecting shoreline habitat, either through increased awareness or application in empirical analyses.

Table 2.1: User-defined values chosen for segmenting lake images in ERDAS Imagine (ERDAS, 2010). The values were chosen to identify edges and combine groups of pixels into objects. The resulting objects were used in the dock analysis workflow to extract areas of the classified image that were potentially docks.

Parameter type	Parameter	Value
Edge detection	Apply image pre-smoothing?	twice
	Difference between pixels	11
	Minimum number of pixels	2
Objects	Minimum value difference of pixels	50
	Variance of pixels	10
	Minimum size	1
	Find narrow strips?	yes

Table 2.2: Confusion matrix for image analysis techniques before and after manual post-processing. Percent accuracy was evaluated for two classes, docks and 'other', using a stratified random sampling design and photo-interpretation of raw images. User's accuracy describes errors of commission and producer's accuracy describes errors of omission. $\hat{K}$ statistics are significantly different from zero ($\alpha = 0.05$) indicating results were not achieved by random chance.

	User's accuracy		Producer's accuracy			
	Docks	Other	Docks	Other	Overall	$\hat{K}$
Before	32.0	99.0	88.9	85.3	85.6	40.8 (28.1 - 53.4)[a]
After	83.8	99.6	93.9	98.7	98.4	87.7 (79.3 - 96.1)

[a]95% confidence interval

Table 2.3: Summary information of dock data for the entire dataset of 4,261 lakes in Minnesota, including summary data after removing 1,930 lakes without docks. Data describe mean (95% confidence intervals), median, and range for dock counts, density (docks per shoreline km), area (m^2), and area scaled by lake area (%).

Summary variable	Mean (95% CI)	Median	Range
Count	25.0 (22.3, 27.7)	1	0, 3641
Count[a]	45.7 (40.9, 50.4)	12	1, 3641
Density	2.4 (2.3, 2.6)	0.3	0, 34.8
Density[a]	4.5 (4.3, 4.7)	2.3	0.1, 34.8
Area	1335.4 (1136.1, 1534.6)	25	0, 325623
Area[a]	2441.0 (2082.8, 2799.2)	457	5, 325623
Area scaled	0.067 (0.063, 0.072)	0	0, 4.2
Area scaled[a]	0.213 (0.202, 0.224)	0.1	0.1, 4.2

[a]Indicates summary data after removing lakes without docks

Table 2.4: Top five lakes for dock count, density (docks per shoreline km), area (m^2), and area scaled (%). County, shoreline perimeter (km), and surface area (km^2) are also shown for each lake.

Lake	County	Perimeter	Surface area	*Count*[a]
Minnetonka	Hennepin	218.7	57.1	3,641
Gull	Cass	74.6	40.3	1,335
Big Sandy	Aitkin	115.2	26.1	1,198
Otter Tail	Otter Tail	38.2	57.0	885
Pokegama	Itasca	93	27.2	874
				Density
Libbs	Hennepin	1.9	0.1	34.8
Upper Prior	Scott	9.9	1.6	31.8
Florida	Kandiyohi	6.9	2.8	31.2
Green	Kandiyohi	19.5	22.5	28.9
Lower Prior	Scott	24.0	3.9	28.2
				Area
Minnetonka	Hennepin	218.7	57.1	325,623
Gull	Cass	74.6	40.3	105,425
Big Sandy	Aitkin	115.2	26.1	85,786
Pelican	Crow Wing	44.7	33.9	62,555
Cross Lake Reservoir	Crow Wing	33.6	7.3	57,798
				Area scaled
Libbs	Hennepin	1.9	0.1	4.2
Rose	St. Louis	2.0	0.2	1.7
Julia	Sherburne	3.7	0.6	1.7
Forest	Hennepin	3.8	0.4	1.6
Upper Prior	Scott	9.9	1.6	1.2

[a]Variables in the far-right column describe docks

Table 2.5: Top five counties and sub-basins (Hydrologic Unit Code level 8) for mean dock density (docks per shoreline km).

County	Mean	Sample size
Steele	13.6	2
Sherburne	9.3	23
Morrison	7.6	23
Crow Wing	6.3	215
Douglas	6.1	63
Sub-basin		
Long Prairie River	7.0	59
Cannon River	5.9	45
Sauk River	5.8	52
Pine River	5.6	148
St. Cloud (Miss. River)	5.6	82

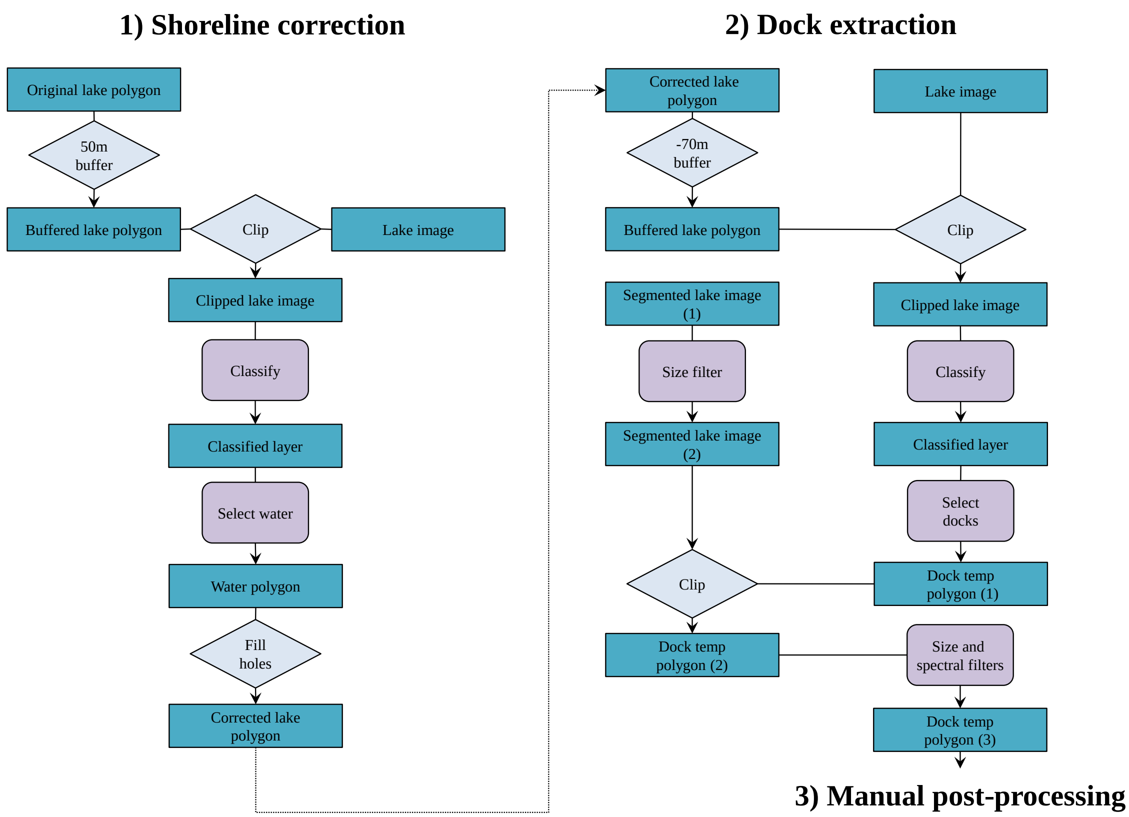


Figure 2.1: Dock analysis workflow used to quantify docks in aerial images. The three processes are shoreline correction, dock extraction, and manual post-processing. The rectangles indicate temporary files, diamonds indicate processing commands, and rounded rectangles indicate algorithms used to identify classes or objects of interest. See listings B.1 and B.2 for complete implementation of the first two processes.

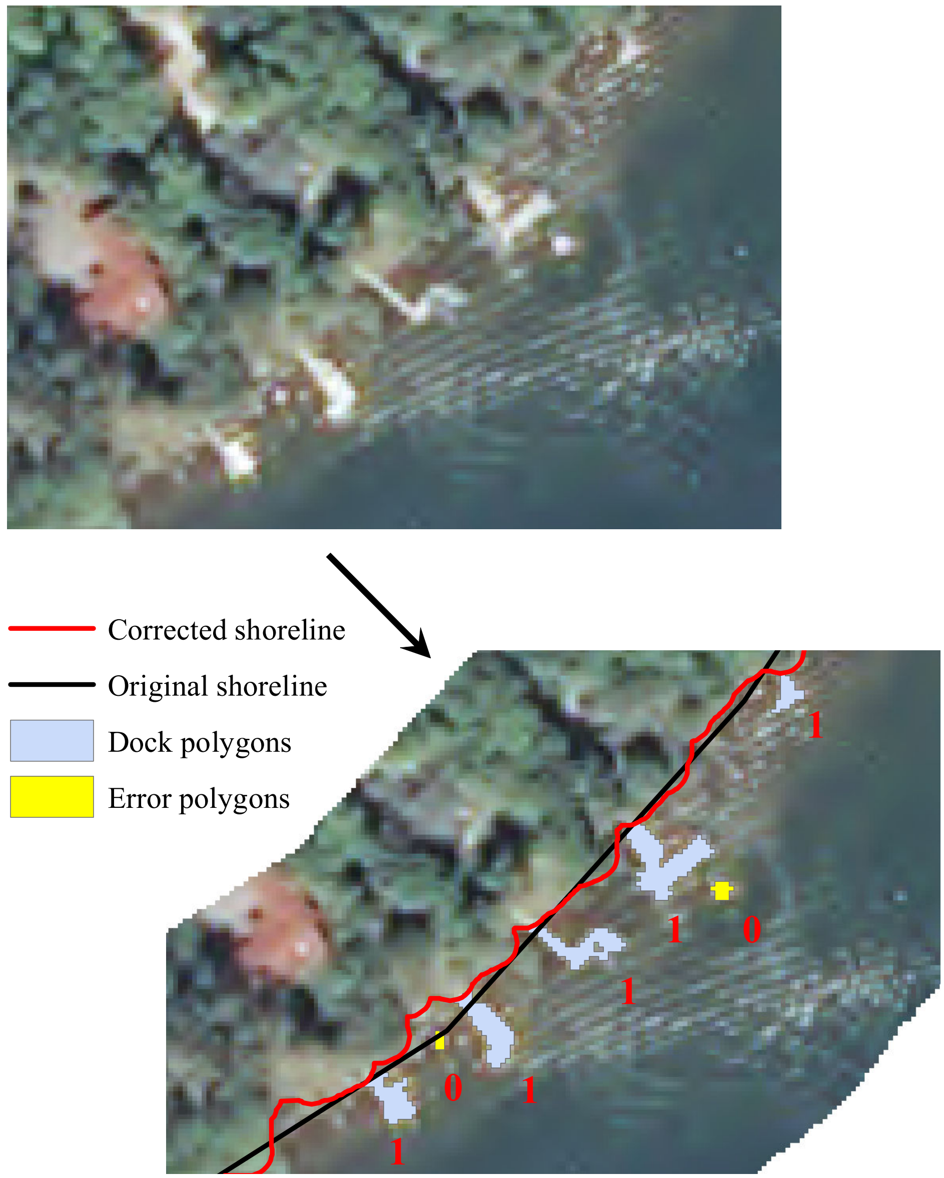


Figure 2.2: Example of output from the dock analysis workflow indicated in fig. 2.1. The top image shows an unprocessed portion of a lake image and the bottom image shows the workflow output. The corrected shoreline is the output from the shoreline correction process and the polygons (both dock and erroneous polygons) are the output from the dock extraction process. Manual post-processing codes the polygons as 1 or 0 if a polygon is a dock or erroneous.

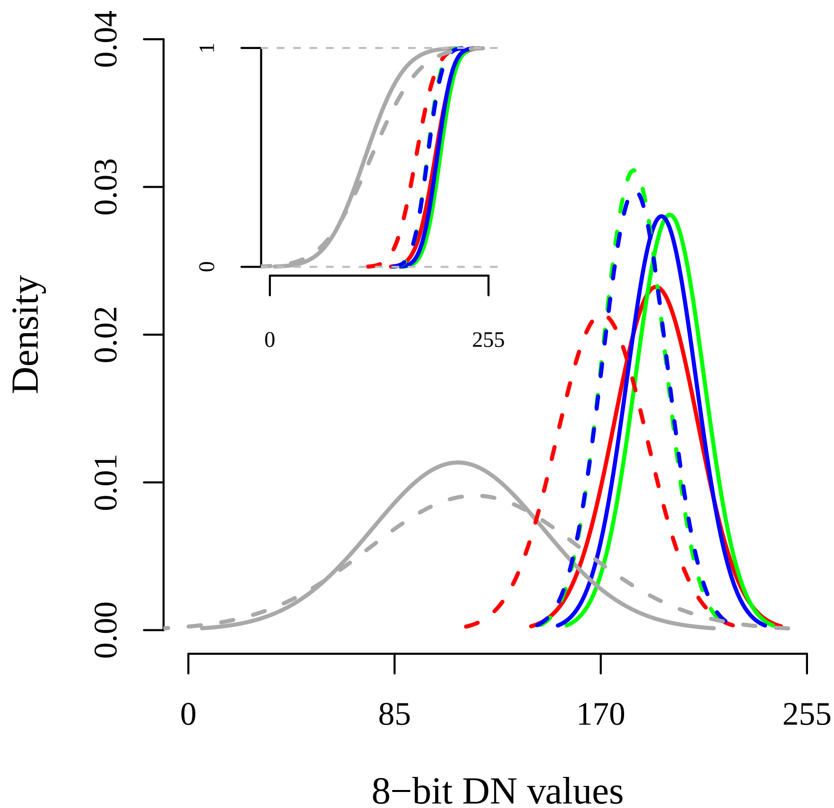


Figure 2.3: Distribution of spectral characteristics of 235,819 polygons identified as docks (solid lines) or erroneous polygons (dotted lines) during post-processing. Curves indicate the distribution of mean pixel values in polygons for the red, green, blue, and near infrared spectral bands and were approximated using a Gaussian normal distribution. The subplot indicates estimated cumulative density functions for each spectral band, also separated by polygon type.

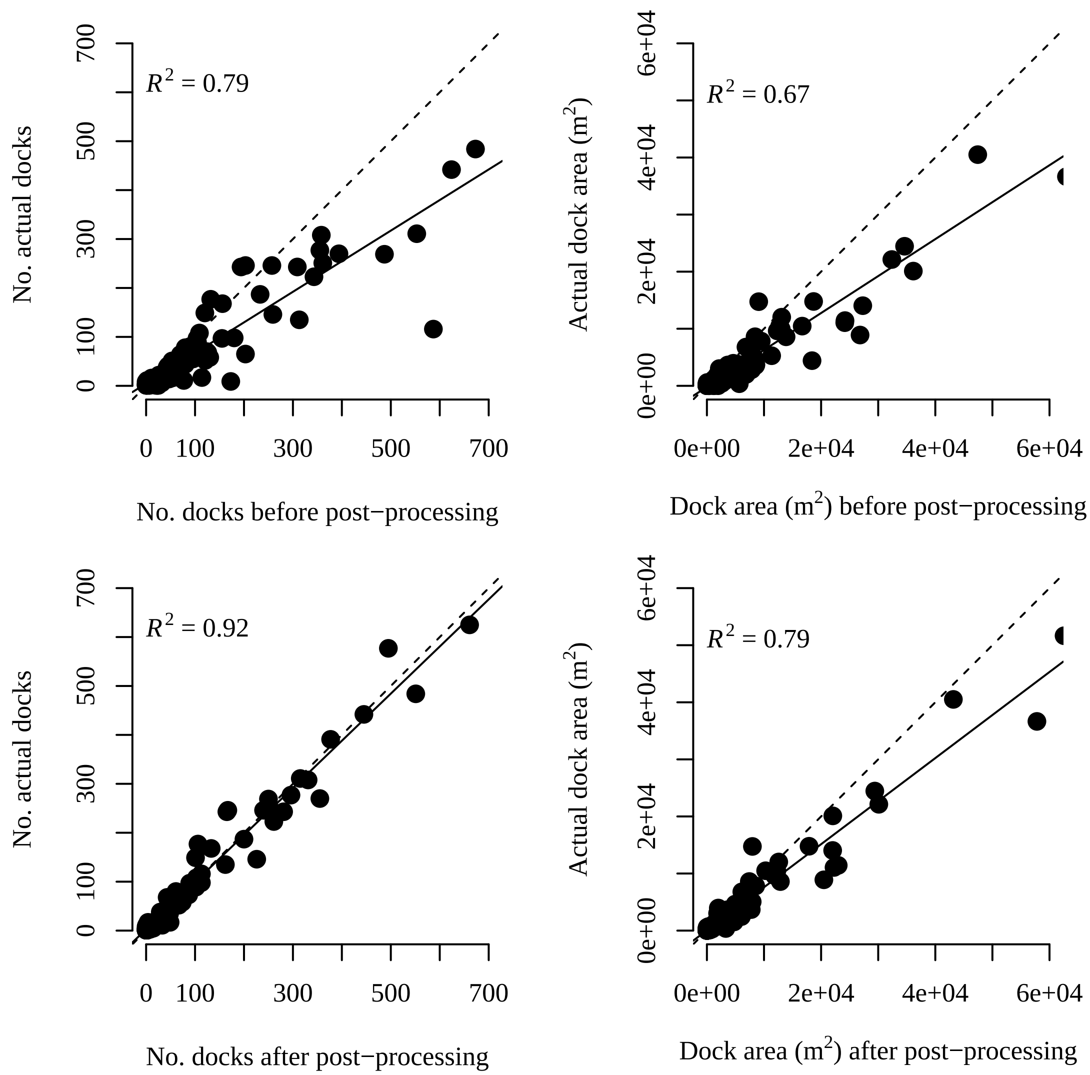


Figure 2.4: True dock data compared to data obtained from image classification. The top two plots compare actual data to number and area of docks prior to post-processing and the bottom two plots compare actual data to data after post-processing. Dashed lines indicate lines through the origin with a slope of one and black lines indicate regression lines. R-squared values were obtained from linear regression models using $\log + 1$ transformed variables. All models had slope estimates that were significantly different from a slope of one ($\alpha = 0.05$, $p < 0.005$ for all).

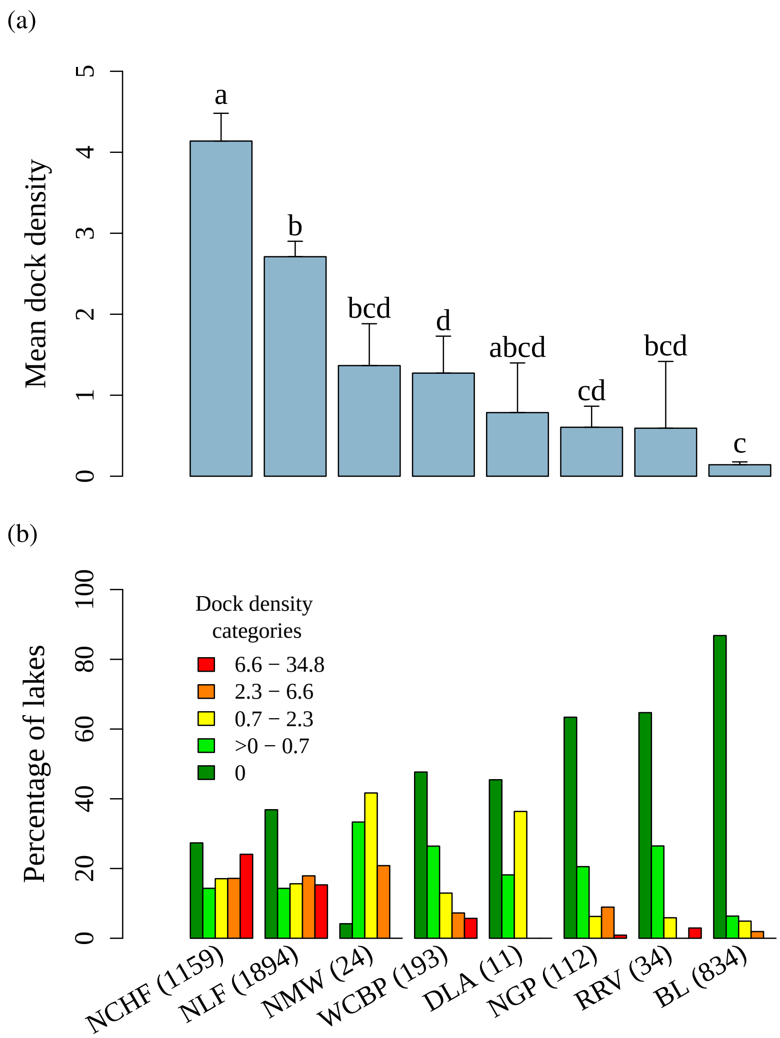


Figure 2.5: Dock densities (docks per shoreline km) summarized by ecoregions (Omernik, 1987). Subfigure (a) indicates mean dock densities with 95% confidence intervals. Differences in mean dock density among ecoregions were evaluated using an ANOVA F-test (F = 68.4, df = 7,4253, $p <$ 0.005) followed by a Tukey multiple pairwise comparison. Ecoregions that share a letter are not significantly different. Subfigure (b) indicates the percentage of lakes within each of five dock density categories for each ecoregion. Categories are based on quintile values for all lakes. Number of lakes evaluated in each ecoregion is shown in parentheses. BL = Border Lakes, DLA = Driftless Area, NCHF = North Central Hardwood Forests, NGP = Northern Glaciated Plains, NLF = Northern Lakes and Forests, NMW = Northern Minnesota Wetlands, RRV = Red River Valley, and WCBP = Western Cornbelt Plains.

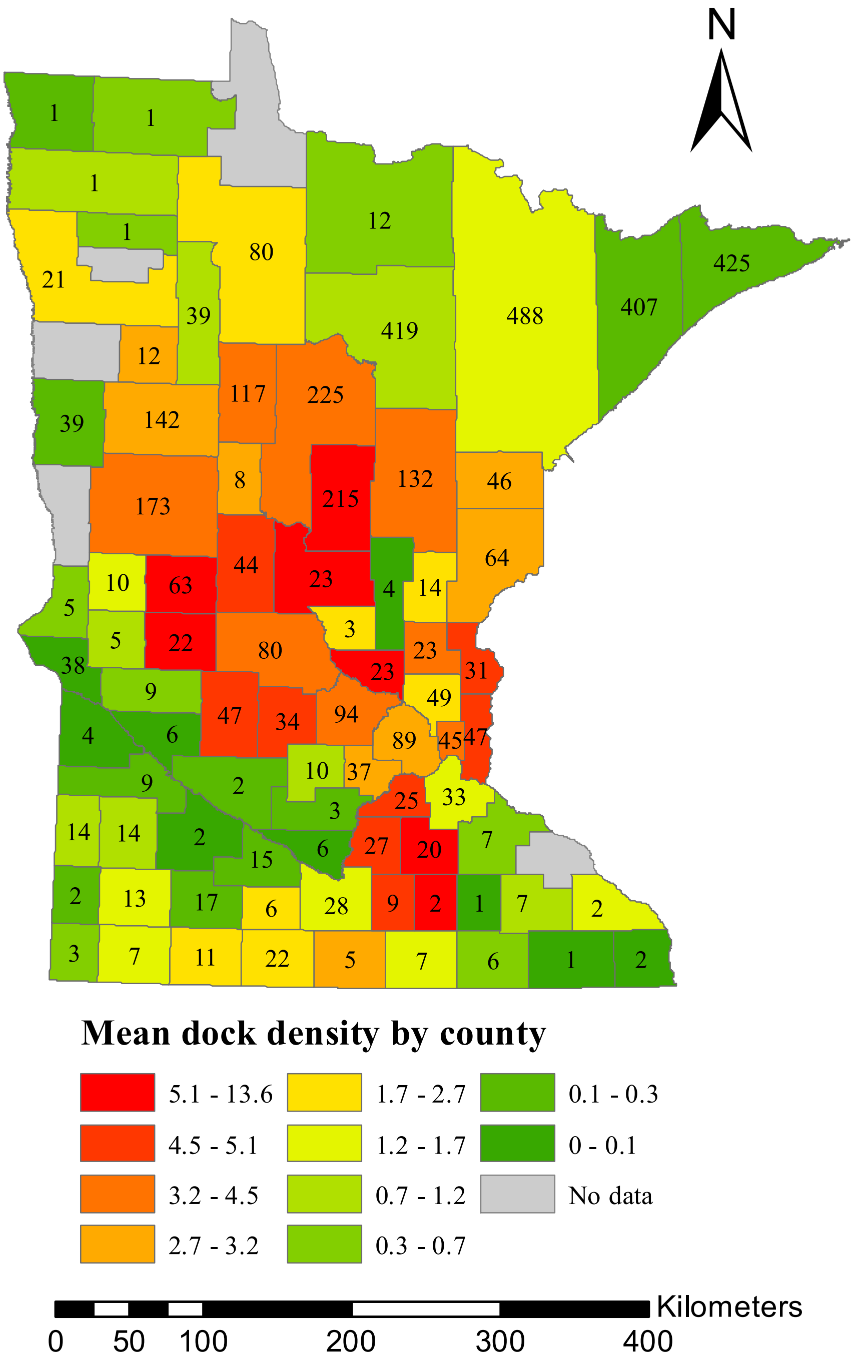


Figure 2.6: Mean dock densities (docks per shoreline km) by county. Density categories indicate decile values for mean dock density by county. Numbers in counties indicate sample size.

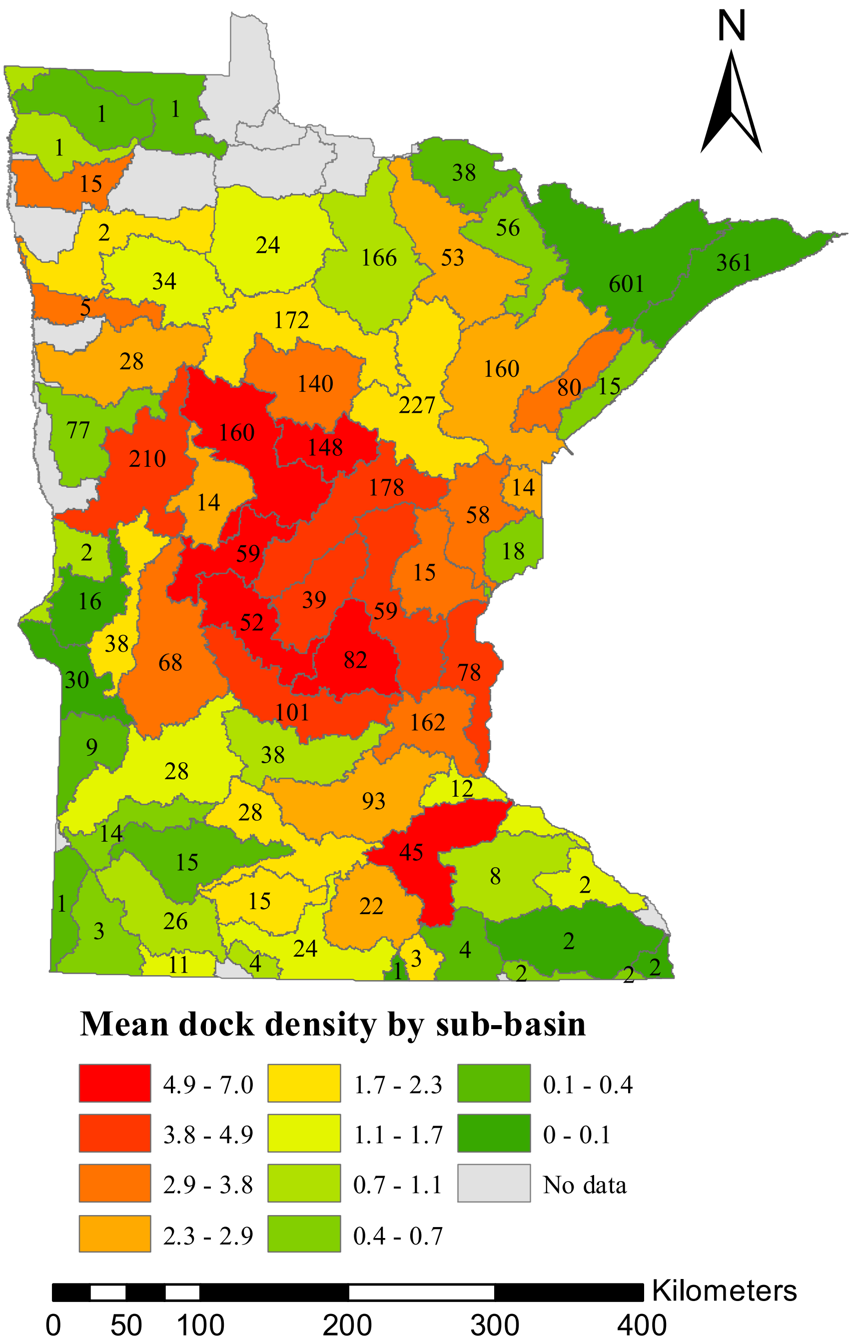


Figure 2.7: Mean dock densities (docks per shoreline km) by sub-basin (Hydrologic Unit Code or HUC level eight). Density categories indicate decile values for mean dock density by sub-basin. Numbers in sub-basins indicate sample size.

Chapter 3

Between- and within-lake responses of macrophyte richness metrics to shoreline development

Abstract

Aquatic habitat in littoral environments can be affected by residential development of shoreline areas. Effects of shoreline development may be manifested at different spatial scales such that site-level effects may induce lake-wide changes in community composition. We evaluated the relationship between macrophyte richness metrics and shoreline development to quantify indicator response at different spatial scales. First, the response of total, submersed, emergent-floating, and sensitive species was evaluated for a set of 1444 lakes throughout Minnesota that exhibit a gradient of shoreline development and limnological characteristics. Generalized Linear Models were developed for the entire dataset and stratified subsets of lakes to control for confounding effects of lake depth and watershed development. Second, the response of total, submersed, and sensitive species to shoreline development was evaluated within lakes to quantify macrophyte response as a function of distance to the nearest in-water structure. Within-lake analyses using Generalized Linear Mixed Models focused on three lakes of comparable size and minimal influence of watershed stressors. Between-lake analyses illustrated clear response of macrophyte richness metrics to increasing shoreline development, such that fewer emergent-floating and sensitive species were correlated with increasing dock density. These trends were particularly evident for deeper lakes with lower development in the watershed. Within-lake analyses indicated that survey points farther from structures had higher total species richness and presence of species sensitive to disturbance. We provide further evidence that shoreline development is associated with reduced aquatic habitat, particularly by illustrating the response of macrophyte richness metrics across multiple lake types and

different spatial scales.

3.1 Introduction

Human activities on the landscape can have notable effects on the goods and services provided by aquatic ecosystems. Inland freshwater lakes, in particular, provide numerous recreational and economic benefits that can be negatively affected by anthropogenic stressors acting at multiple spatial scales (Carpenter et al., 1998a; Dodds et al., 2009; Wang et al., 2010). Numerous studies have focused on the effects of nonpoint source pollution associated with watershed development (Carpenter et al., 1998a,b), although human activities at the local scale can also affect the services provided by freshwater lakes (Post et al., 2002; Radomski et al., 2010). Recent efforts to better understand the relationship between human activities and lake resources have focused on evaluating the potential effects of shoreline development. The increasing presence of seasonal or permanent homes on lake shorelines and the associated alteration of habitat has been documented by several researchers in the last twenty years (Bryan and Scarnecchia, 1992; Christensen et al., 1996; Radomski and Goeman, 2001; Jennings et al., 2003; Gaeta et al., 2011). Quantifying the explicit relationships between human activities at multiple spatial scales and the functional and structural properties of natural systems is an essential process for developing effective resource management plans.

The potential effects of shoreline development are of concern because littoral areas in freshwater lakes represent critical habitat for numerous species. Littoral areas support important nursery and spawning areas for fish (Hunt and Annett, 2002; Reed and Pereira, 2009), provide structure for aquatic invertebrates (Tolonen et al., 2001; Jurca et al., 2012), and serve as important waterfowl production areas (Lauridsen et al., 1993; Knapton and Petrie, 1999). The colonization of shoreline areas by aquatic macrophytes also promotes the maintenance of a clear-water stable state by improving water clarity through sediment retention, filtering nutrients, and dampening physical effects of wave action (Scheffer et al., 1993). Residential development of shoreline areas is often accompanied by habitat degradation and changes in water quality as homeowners alter nearshore assemblages to create more desirable shoreline property that mimics urban and suburban lawns. Shoreline development has been implicated in the removal of emergent and floating-leaf vegetation (Radomski and Goeman, 2001; Jennings et al., 2003) and a reduction in coarse woody structure (Christensen et al., 1996; Francis and Schindler, 2006; Marburg et al., 2006). Alteration of shoreline habitat can also affect fish and other trophic levels via bottom-up mechanisms (Bryan and Scarnecchia, 1992; Jennings et al., 1999; Schindler et al., 2000; Reed and Pereira, 2009; Brauns et al., 2011; Gaeta et al., 2011). For example, Reed and Pereira (2009) examined the effects of shoreline development on nest site selection for black crappie (*Pomoxis nigromaculatus*) and largemouth bass (*Micropterus salmoides*) and found that nest locations were relegated to sub-optimal habitat as a result of vegetation removal near swimming beaches and docks. Additionally, Brauns et al. (2011) found that littoral food webs in developed areas of lake shoreline were substantially less complex with lower diversity of food resources and consumers. Terrestrial and aquatic habitat degradation associated with development were considered primary factors limiting trophic network connectivity.

An evaluation of the potential effects of shoreline development should consider useful indicators that are not only responsive to anthropogenic stressors but also have ecological significance within the larger lake community. Aquatic macrophytes, in particular, are responsive to the effects of shoreline development (Radomski and Goeman, 2001; Jennings et al., 2003) and provide critical ecological services that support and maintain multiple trophic levels (Scheffer et al., 1993; Jeppesen et al., 1998). For example, emergent and floating-leaf species that occur in shallower areas of the littoral zone may serve as diagnostic indicators of habitat degradation from shoreline development (Radomski and Goeman, 2001). Emergent vegetation also reduces sediment resuspension rates and can serve a critical role in removing organic matter and nutrients from wastewater runoff (Ansola et al., 1995; Horppila and Nurminen, 2001). Conversely, submersed species may be more responsive to changes in water clarity due to variable tolerances to light reduction and also may be more important mediators of lake-wide trophic condition than other growth forms (Scheffer et al., 1993). Accordingly, the response of macrophytes to multiple stressors has supported their use in the development of biotic indices of lake condition, using both multimetric and single indicator approaches (Nichols, 1999; Beck et al., 2010; Radomski and Perleberg, 2012). Despite the utility of macrophytes as environmental indicators, lack of consensus regarding the most appropriate diagnostic measure has lead to a proliferation of techniques for biological assessment (Beck and Hatch, 2009). Additionally, in the absence of exhaustive biological surveys, more simplistic measures of ecological health may provide the most practical measure to evaluate potential impacts of environmental stressors. For example, species richness may be the most practical indicator because it can be determined with relatively minimal sampling effort and is also responsive to changes in lake condition (Rorslett, 1991; Sass et al., 2010; Radomski and Perleberg, 2012).

Useful environmental indicators should serve as accurate proxy measures of ecosystem complexity and, therefore, should be responsive to environmental changes at multiple spatial scales (Niemi and McDonald, 2004). However, studies that have evaluated the potential effects of shoreline development have primarily focused on limited spatial scales, and have generally not compared biological response in different spatial contexts. For example, a common approach is to quantify shoreline development at different sites within the same lake and then compare biological assemblages between sites (e.g., Bryan and Scarnecchia, 1992; Reed and Pereira, 2009). Although quantifying within-lake effects of shoreline development has importance for site-level management, cumulative and incremental increases in shoreline development may induce lake-wide changes in environmental condition. For example, changes in coarse woody structure and macrophyte abundance in response to cumulative lake-wide effects of habitat modification, in addition to site-level effects related to shoreline development were documented by Jennings et al. (2003). Additionally, the few studies that have evaluated effects of shoreline development across multiple lakes have only evaluated a limited number of lakes due to the logistical challenges of quantifying shoreline development at numerous locations (e.g., Scheuerell and Schindler, 2004; Francis and Schindler, 2006). One exception is an evaluation of lake-wide effects of shoreline development on littoral habitat for 332 lakes using data from *in situ* observations of lake condition Wehrly et al. (2012). Studies evaluating lake-wide and potential cumulative effects of shoreline development should consider large sample sizes that capture the gradient of different lake types in a given management region, in addition to site-level comparisons to evaluate the range of indicator responses to shoreline development at different scales.

The goal of the current study is to evaluate the response of littoral macrophyte assemblages to shoreline development by considering appropriate indicators and different spatial scales. Specifically, we evaluate the response of various macrophyte richness metrics between and within lakes to identify relevant spatial scales at which shoreline development may significantly alter community composition using Generalized Linear Models (GLM) and Generalized Linear Mixed Models (GLMM) when appropriate. Species richness is chosen as an appropriate indicator of biological response given the abundance of available surveys from which species lists for individual lakes can be obtained. First, we evaluate between-lake effects of shoreline development on a set of 1444 lakes that cover a gradient of anthropogenic stressors and natural limnological characteristics. Second, we evaluate within-lake effects of shoreline development on three lakes using the response of macrophyte richness metrics at individual survey points to distance from the nearest structure. For all analyses, docks and other shoreline structures are used as indicators of direct and indirect effects of shoreline development. Numerous studies have illustrated the appropriateness of docks as adequate proxy measures for a majority of stressors related to shoreline development (Radomski et al., 2010; Wehrly et al., 2012). Our results will provide additional information on the effects of shoreline development, particularly in the context of multiple lake types and the cumulative effects of aquatic habitat degradation at different spatial scales.

3.2 Methods

3.2.1 Between-lake effects of docks

Between-lake effects of docks on macrophyte richness metrics were evaluated using vegetation surveys from the Minnesota Department of Natural Resources (MNDNR, Reschke et al., 2006). The dataset included macrophyte surveys for 1444 lakes throughout Minnesota (fig. 3.1), collected early July to late August from 1992 to 2003. Surveys were conducted using a 'modified belt transect method' with transects perpendicular to the shoreline and extending to the maximum depth of plant growth (Anon, 1993). Transect number varied (10–50) with lake size with larger lakes receiving greater sampling effort. Macrophytes within ten feet of each side of the boat along a transect were visually identified to species and categorized by growth form using Fassett (1957) and Borman et al. (2001). Sensitive species were identified as having coefficient of conservatism values (C, from Milburn et al. 2007) greater than seven (*sensu* Beck et al., 2010). C values range from zero to ten and describe the estimated probability that a plant is likely to occur in a landscape that is believed to be relatively unaltered from presettlement conditions (Swink and Wilhelm, 1994; Nichols, 1999).

GLMs were used to evaluate potential effects of docks between lakes (McCullagh and Nelder, 1989; Zuur et al., 2009). The four response variables were total species richness, and richness of submersed, emergent/floating-leaf, and sensitive species at each lake. Previous research has suggested that emergent and floating-leaf species (hereafter referred to as emergent-floating) are useful indicators of shoreline development because of preferential removal by homeowners as a result of greater frequency of occurrence in shallow areas (Radomski and Goeman, 2001; Jennings et al., 2003). Accordingly, these species were grouped to evaluate the hypothesis that the richness of emergent-floating species may be a useful indicator of the effects of shoreline development. All response variables were modeled using a Poisson distribution (log-link) such that $Y_i \sim P(\mu_i)$, where Y_i is observation i from a Poisson random variable Y with $\mathrm{E}(Y_i) = \mu_i$ and $\mathrm{Var}(Y_i) = \mu_i$ (Zuur et al., 2009). The following GLM was used for each response variable (following notation in Zuur et al. 2009):

$$\begin{aligned} \log(\mu_i) &= \eta(X_{i1}, \ldots, X_{iq}) \\ &= \alpha + \beta_1 \times X_{i1} + \ldots + \beta_q \times X_{iq} \end{aligned} \tag{3.1}$$

where μ_i is the expected value of Y for observation i determined as a function of q predictor variables and a vector of associated parameters, η (i.e., α, β_1, ..., β_q). The `glm` function in the `stats` package in program R (RDCT, 2013) was used to identify parameter values using maximum likelihood estimation (Venables and Ripley, 2002). Models that evaluated submersed, emergent-floating, and sensitive species included total species richness (log-transformed) as an offset variable to account for different species richness between lakes (Fox and Weisberg, 2011). Offset variables with parameter values significantly different from one were included as actual variables in each model.

Explanatory variables quantified for each lake included dock density (docks per shoreline kilometer, log-transformed), surface area (hectares, log-transformed), maximum depth (meters, log-transformed), trophic state index (TSI), and the proportion of watershed land as urban, agricultural, or forested (table 3.1). These variables represent an *a priori* identified list of natural lake characteristics and human-induced stressors hypothesized to influence aquatic plant assemblages. Dock density was obtained using pixel-based classifiers and object-based image analysis techniques to extract dock polygons from high-resolution aerial photos (see chapter 2 for more information, Jensen et al. 2009; Blaschke 2010). Surface area and maximum depth were obtained from Geographical Information System (GIS) shapefiles (MNDNR, 2012a) and an online lake database maintained by MNDNR[1]. TSI values provided an indication of lake productivity and were calculated using equations in Carlson (1977) and water quality data from STORET (accessed via MNPCA, 2012). Missing water quality information from STORET was supplemented using satellite-derived water transparency measurements (Olmanson et al., 2008)[2]. Land use variables from the 2001 National Land Cover Database (Homer et al., 2007) were summarized using principal component analysis (PCA) to reduce data dimensionality. The first PCA axis (PC1) was used for analysis and explained 62.2% of the variance among the land use variables. Loadings on the first axis were 0.29 for urban, 0.64 for agriculture, and -0.71 for forest.

Model development for each of the four response variables (total, submersed, sensitive, and emergent-floating species richness) followed a backwards stepwise selection approach that began with an initial model with all explanatory variables and their second-order interactions. Sequential models were evaluated by dropping individual terms and retaining the model that had the lowest Akaike Information Criterion (AIC) value (Akaike, 1973). The `step` function in the `stats` package of program R (RDCT, 2013) was used for model selection (Venables and Ripley, 2002; Fox and Weisberg, 2011). The optimal model for each response variable was validated by examining Pearson and deviance residual plots to assess patterns, variance, and outliers (Pierce and Schafer, 1986;

[1] http://www.dnr.state.mn.us/lakefind/
[2] Data available at http://water.umn.edu/lakebrows.html

Zuur et al., 2009). Pearson residuals provide an analysis of model fit when deviation may vary as a function of the predicted values, whereas deviance residuals provide an indication of the contribution of each observation to overall model deviance. The predictive ability of each model was evaluated using the explained deviance, calculated as the difference between the null deviance and the residual deviance, divided by the null deviance (Zuur et al., 2009; Fox and Weisberg, 2011). Lastly, effects plots (`effects` package, Fox and Weisberg 2011) were used to illustrate the specific effects of relevant explanatory variables for specific models. Effects plots allow an interpretation of the effects of a single explanatory variable (usually high-order terms) on a response by calculating the fitted values of an estimated model across the range of values for the variable while holding all other variables constant.

Species richness is affected by several natural and anthropogenic factors that act across different spatial and temporal contexts (Rorslett, 1991; Sass et al., 2010). Accordingly, an evaluation of the effects of a single variable, such as dock density, is difficult in the context of other variables that may affect species richness. We used two approaches for model development to account for the influence of multiple variables. First, we evaluated the entire dataset of 1444 lakes and included all explanatory variables. Second, we developed models using stratified subsets of the entire dataset to control for the potential effects of lake depth and watershed development (table C.1 and fig. 3.1). Stratification of the dataset produced four groups of lakes: 1) shallow lakes with low watershed development (n = 439); 2) deep lakes with low watershed development (n = 414); 3) shallow lakes with high watershed development (n = 352); and 4) deep lakes with high watershed development (n = 239). A maximum depth of 10 m was used as a threshold because glacial lakes with maximum depths greater than ($>$) 10 m are typically dimictic, whereas shallower lakes are polymictic. This threshold describes lakes with different rates of internal nutrient loading caused by sediment resuspension during mixing.

The development threshold was defined as the summed percentage of watershed land use as urban and agriculture, such that lakes with percentages $>$ 25% had developed watersheds and lakes less than ($<$) 25% had undeveloped watersheds. This threshold is used by MNDNR to identify lake protection/restoration priorities (T. Cross, MNDNR, January 2013, pers. comm.). Depth and land use were not used as explanatory variables in the models for the stratified datasets. A total of twenty models were developed: sixteen for the four stratified subsets (four response variables per subset) and four for the entire dataset (one for each response variable).

3.2.2 Within-lake effects of docks

Within-lake effects of docks on macrophyte richness metrics were evaluated using surveys for three different lakes near Saint Paul, Minnesota: Christmas (Hennepin County) and Jane and Square (Washington County) (fig. 3.2). Each lake is similar in size (~100 ha), maximum depth (~20 m), trophic state (mesotrophic), and species composition, making them suitable for comparison. Point intercept surveys were conducted in late summer of 2008 for Christmas and Jane lakes and late summer of 2006 for Square lake. Surveys were established within a grid of evenly spaced points that covered the entire littoral zone of each lake (Madsen, 1999). In addition to depth, species were enumerated and identified at each point using a double-sided rake (table 3.2). Point density (sampling effort) was approximately 8.5 points per littoral hectare and was sufficient to obtain an accurate estimate of total species richness (Beck et al., 2010). All plants at each point were identified to species and growth form using methods in section 3.2.1. The distance of each point to the nearest dock was quantified as a primary measure of the potential effects of shoreline development (table 3.2 and fig. 3.2). Both depth and distance to nearest dock for each point were log-transformed.

GLMMs were used to determine whether the distance to the nearest structure had a significant effect on macrophyte response variables for each survey point. GLMMs can be used to model linear fixed effects of predictors while also incorporating a random effect of an *a priori* defined variable in the variance structure of the model (Zuur et al., 2007, 2009). The general notation for a mixed effects model of a Poisson-distributed response variable is:

$$\begin{aligned} \log(\mu_i) &= \eta(X_{i1}, \ldots, X_{iq}) + a_j + b_j \times Z_{ij} \\ &= \alpha + \beta_1 \times X_{i1} + \ldots + \beta_q \times X_{iq} + a_j + b_j \times Z_{ij} \end{aligned} \tag{3.2}$$

where μ_i is the expected value of Y for observation i determined as a function of fixed effects (for q variables) and a random effect (for one variable with j levels, varying as a function of predictor Z). The vector η defines the associated parameters (α, β_1, . . ., β_q) for the fixed effects and a and b define the parameters for the random component not included in the mean response. A random effect can also be modeled using only a random intercept and would be defined only by a_j, rather than also varying as a function of another predictor variable (random intercept and slope model). Accordingly, model selection followed an approach where the optimal random component of each model was determined (random intercept and slope, random intercept, no effect), followed by identification of the optimal structure of the fixed effects (Zuur et al., 2009). In all cases, the lake identifier (as a factor) was used as a random effect. All models were developed using the `glmer` function in the `lme4` package (parameter estimation via the Laplacian approximation, Tuerlinckx et al. 2006; Doran et al. 2007).

Total and submersed species richness and sensitive species presence/absence at each point were evaluated as response variables for three different models. Richness of emergent-floating species was not evaluated because very few species of these growth forms were observed in the three study lakes. Total and submersed species richness were evaluated as Poisson random variables (log-link) as in section 3.2.1. Sensitive species richness was not modelled as a Poisson random variable because survey points rarely had more than one sensitive species. As such, sensitive species richness was evaluated as presence/absence using a binomial random variable (logit-link or $\log(\frac{\pi_i}{1-\pi_i})$) such that $Y_i \sim B(1, \pi_i)$, where Y_i is observation i from a Binomial random variable Y with $\mathrm{E}\left(Y_i\right) = \pi_i$ and $\mathrm{Var}\left(Y_i\right) = \pi_i \times (1 - \pi_i)$ (Zuur et al., 2009). Models that evaluated submersed species richness included total species richness (log-transformed) as an offset variable in the predictor terms (Fox and Weisberg, 2011). Model assumptions were evaluated using methods similar to those described in section 3.2.1. Additionally, model performance was evaluated by regressing the observed response values against the fitted values and determining the R^2 value of the resulting linear model (hereafter referred to as pseudo-R^2). This measure should be considered a rough approximation of model performance due to lack of consensus regarding the appropriateness of R^2 values to evaluate GLMMs (Tuerlinckx et al., 2006; Edwards et al., 2008). Lastly, effects plots were used to illustrate the specific effects of explanatory variables on response variables for relevant models.

We evaluated the potential for spatial correlation among survey points for each lake to determine if a spatial correlation structure was required for model development (e.g., Dale et al., 2002; Perry et al., 2002). The residuals of the best-fitting model for each response variable were examined for each lake using spherical semivariograms (Burrough and McDonnell, 1998; Bivand et al., 2008). Maximum lag distances were equal to one third the diagonal distance between the range of coordinate values of each lake and lag tolerances were determined as the maximum lag distance divided by fifteen. Evidence for spatial correlation among survey points was determined by comparing the semivariogram model for each lake to null models created by randomizing residual values to create bootstrapped null models ($n = 1000$). Semivariance models were also evaluated using semivariogram clouds to identify outliers or lag distances with unusual variability (Bivand et al., 2008). The functions `variogram` and `vgm` of the `gstat` package (Pebesma, 2004) were used.

3.3 Results

3.3.1 Between-lake effects of docks

Data summary and model performance

A total of 188 unique species were identified in the dataset of 1444 lakes used to evaluate the between-lake effects of docks. Of these species, 75 were submersed, 58 were emergent-floating, and 43 were sensitive. An average of 20.5 species were found in each lake, with richness values ranging from one to 64 (table 3.1). On average, approximately half of the species at each lake were submersed, one-third were emergent-floating species, and less than 15% were sensitive species. Trends in richness metrics were similar for the stratified subsets of lakes such that submersed, emergent-floating, and sensitive species represented decreasing proportions of total richness (table C.1). However, total species richness varied among the stratified subsets. A two-way analysis of variance (ANOVA) for total species richness (using depth and watershed development categories as factors) indicated that species richness varied significantly among the four subsets of lakes ($F =$ 240.1, $df =$ 2, 1439, $p <$ 0.005), such that lake depth had a positive relationship and watershed development had a negative relationship with total species richness. Average dock density for all lakes was 4.5 docks per shoreline km, with values ranging from 0 to 31.2 (table 3.1). Average dock density varied significantly among the subsets of lakes such that higher dock density was associated with deeper lakes and higher watershed development (two-way ANOVA, $F =$ 91.8, $df =$ 2, 1439, $p <$ 0.005).

Model performance varied for evaluations of all lakes and stratified subsets of lakes, in addition to variable performance among macrophyte response variables (table C.2). The model with the highest performance was total species richness in all lakes (0.46 explained deviance) and the model with the lowest performance was emergent-floating species in deep lakes with low development (0.05 explained deviance). In general, analyses that evaluated all lakes outperformed models that evaluated subsets of lakes, although this result may be attributed to larger sample size and inclusion of depth and PC1 as explanatory variables for all lakes. The average explained deviance was 0.31 for models that evaluated all lakes and 0.15 for models that evaluated subsets of lakes. Additionally, model performance among the different response variables indicated that performance decreased sequentially for total (0.27 mean explained deviance among all models), sensitive (0.21), submersed (0.17), and emergent-floating species richness (0.09). These trends were generally consistent for all model types (all or stratified).

Effects of shoreline development

GLM results for the entire dataset of 1444 lakes indicated that dock density had a consistent but variable influence on richness metrics. For each response variable, dock density was included as a significant predictor variable in the optimal model, either as a main effect or as a second-order interaction with other explanatory variables (tables 3.3 and C.3). Models that included dock density as a significant main effect were those that evaluated submersed, emergent-floating, and sensitive species richness. Dock density was also included as a significant interaction term with PC1 for emergent-floating species and with maximum depth, TSI, and PC1 for sensitive species. Dock density was included as a significant variable for total species richness only in the interaction with surface area, TSI, and PC1. Other important explanatory variables were also included as main effects. Models included significant main effects for surface area, TSI, and PC1 for total species richness, surface area and TSI for submersed species, PC1 for emergent-floating species, and surface area, maximum depth, and TSI for sensitive species.

Among the stratified subsets of lakes (fig. 3.1), dock density generally had a positive effect on total and submersed species richness and a negative effect on emergent-floating and sensitive species richness (tables 3.3 and C.4 to C.7). However, the specific effects were intensified with decreasing watershed development, such that dock density was significantly related to every richness metric for lakes with low watershed development. Dock effects were marginally higher with increasing lake depth, such that analyses comparing richness metrics in the low watershed development category had slightly stronger relationships with dock density in deeper lakes. Dock effects were less pronounced for lakes with high watershed development for both depth categories.

Deep lakes with low watershed development may be particularly affected by shoreline development between-lakes. Accordingly, effects plots for these lakes (fig. 3.3) illustrate the main effects of dock density on total, submersed, emergent/floating, and sensitive species richness. Additionally, fig. 3.4 illustrates effects plots for second-order interactions of dock density with lake area for total species richness. The positive association of total species richness with increasing dock density is more pronounced in smaller lakes, with the trends decreasing as lake size increases.

3.3.2 Within-lake effects of docks

Data summary and model performance

A total of 43 different species were identified in the three study lakes used to evaluate potential within-lake effects of docks. Among these species, 28 were submersed and only three were sensitive. Jane lake had the highest total species richness (31), Christmas lake was intermediate (29), and Square lake had the lowest (24). Mean total species richness among survey points was 2.7 with values ranging from zero to 11. Mean values for submersed and sensitive species richness among survey points were approximately 85% and 10% of mean total species richness (table 3.2). Average richness for total, submersed, and sensitive species for points within lakes were significantly different between lakes (one-way ANOVA, $p < 0.005$ for all comparisons), indicating that the use of a random lake component in GLMMs was justified. A comparison of average distance of each point to the nearest structure also indicated differences among lakes (ANOVA, $F = 50.0$, $df = 2, 1004$, $p < 0.005$), such that average distance was lowest for Christmas lake, intermediate for Square lake, and highest for Jane lake.

Model performance for the optimal GLMMs indicated that most models explained a sufficient amount of variation among the response variables (table C.8). Interestingly, models with the lowest performance were those that evaluated total species richness (pseudo-R^2, 0.24). Models for total species richness also exhibited a partial prediction bias towards higher estimated fitted values relative to observed as indicated by slope values less than one (0.92). Models that evaluated submersed species indicated exceptional model performance regardless of the analysis (pseudo-R^2, all 0.90), although high-performance cannot be attributed to any of the explanatory variables (see below). Models that evaluated sensitive species exhibited moderate performance relative to the other analyses (pseudo-R^2, 0.42). Analyses of spatial dependence indicated that similarity among survey points as a result of spatial correlation was negligible.

Effects of shoreline development

Optimal models for each response variable in each dataset indicated that a random intercept for each lake was appropriate. That is, the response variable was significantly different among the three study lakes in the mean response, although this response was not conditional on other explanatory variables. This random effect structure is similar to that in eq. (3.2), with the exception that only the random intercept is included. The optimal structure of fixed effects varied for each response variable (tables 3.4 and C.9). Models that evaluated total species richness and sensitive species presence/absence included distance to nearest structure as a significant variable, including significant interactions with survey point depth. For submersed species, model performance was a function of only random effects related to between-lake differences because no response variables were significant as fixed effects for any of the models. Additionally, distance to the nearest structure was positively related to total species richness and sensitive species presence/absence. Conversely, depth was negatively related to total species richness and positively related to sensitive species presence/absence. Effects plots illustrated the unique effects of distance to nearest structure on total species richness and sensitive species presence/absence (fig. 3.5). The association of total species richness and sensitive species presence/absence with distance to nearest structure is most evident at shallow depths (fig. 3.6, similar for sensitive species, fig. C.1).

3.4 Discussion

3.4.1 Interpretation of between- and within-lake effects

The growing body of literature focused on characterizing the effects of shoreline development has consistently described a negative relationship between localized stressors associated with development and the quality of aquatic habitat (Bryan and Scarnecchia, 1992; Christensen et al., 1996; Radomski and Goeman, 2001; Gaeta et al., 2011). Our results corroborate the findings of similar studies by quantifying a negative response of macrophyte assemblages to docks at different spatial scales. Specifically, we have illustrated that 1) macrophyte richness metrics calculated for lake-wide assemblages show predictable responses to increasing gradients of dock density between-lakes and 2) macrophyte richness metrics calculated at individual survey points within-lakes show predictable responses to distance from the nearest structure. Additionally, our analyses considered other covariates that were expected to influence macrophyte assemblage composition and their inclusion as significant variables illustrates the importance of evaluating multiple lake characteristics when developing predictive models with ecological relevance. Although these conclusions generally support previous research, our use of a large dataset of macrophyte surveys and previously unavailable data on dock density (see chapter 2) greatly increases the confidence in interpretations of the effects of shoreline development on aquatic habitat. No other studies have evaluated a comparable dataset using spatially referenced dock data to our knowledge.

The between-lake analyses have indicated that increasing shoreline development can have lake-wide, cumulative effects on macrophyte assemblages, although this effect varies by growth form and species sensitivity. Generally, increasing shoreline development was negatively associated with emergent-floating and sensitive species richness and positively associated with total and submersed species richness. Our analysis of macrophyte richness metrics considered different growth forms as diagnostic of the effects of shoreline development. Individual growth forms represent groups of species with similar physical characteristics and ecological requirements (Sculthorpe, 1967). Accordingly, these similarities have led researchers to hypothesize that competitive abilities among macrophytes can be more accurately characterized by differences among growth forms rather than particular species (Goldberg and Werner, 1983). Our results that suggested different growth forms have variable vulnerability to shoreline development are, therefore, not surprising considering that macrophyte growth forms may exhibit different responses to stressors as a result of different ecological requirements. The specific response of emergent-floating species to nearshore development suggests that vulnerability of a species to shoreline development could primarily be explained by depth of colonization. Emergent and floating-leaf species colonize shallow areas of lakes and are often preferentially removed by homeowners due to visibility and shoreline proximity (Radomski and Goeman, 2001). Conversely, submersed species colonize areas that are, on average, deeper than emergent-floating species and their vulnerability to shoreline development is expected to be reduced. However, the positive association of total and submersed species richness with shoreline development in our results was unexpected and warrants additional research. The increase in submersed species richness, which may be correlated with total species richness, could be the result of competitive exclusion of emergent-floating leaf species mediated by shoreline development.

The between-lake effects of shoreline development also varied among different lake types stratified by maximum depth and watershed development. Although models that evaluated the stratified lake groups had lower performance than those that evaluated all lakes, consistent trends were observed. Specifically, shoreline development exhibited the strongest relationships with macrophyte richness metrics for deep lakes that had relatively undeveloped watersheds. This effect was pronounced in smaller lakes. Most studies that have evaluated shoreline development have focused on specific groups of lakes to minimize the confounding effects of lake characteristics that may influence interpretation of results. Scheuerell and Schindler (2004) examined spatial distribution of fishes along residential gradients and selected 23 lakes with similar characteristics to control for the potential effects of geology, elevation, lake size, and morphometry. Christensen et al. (1996) evaluated coarse woody habitat along a gradient of cabin density by selecting 16 lakes of similar size and low watershed development. Our use of a large dataset differed from previous research and necessitated the stratification of analyses to control for the confounding effects of depth and watershed development. Stratification by these variables was based on relationships with trophic state such that deeper lakes with low watershed development tend to have higher water clarity and improved growing conditions for macrophytes. The significance of lake depth and watershed development in the analyses that evaluated all 1444 lakes reflects these relationships. Furthermore, the finding that macrophyte assemblages in deeper lakes with low watershed development may be more vulnerable to shoreline development is significant and suggests lake depth and watershed characteristics are perhaps larger determinants of macrophyte composition as compared to more localized stressors originating from shoreline areas. Understanding the relative roles of stressors that act at different spatial scales is essential for developing lake-wide management plans. Management of degraded macrophyte assemblages may be most effective if an assessment of water quality issues related to watershed development is conducted prior to evaluating potential effects of shoreline development.

The response of macrophyte richness metrics within-lakes also indicated significant effects of shoreline development on aquatic habitat. Survey points farther from docks were more likely to have higher species richness and contain sensitive species. Interestingly, distance was not related to submersed species richness and contradicts the between-lake analyses that suggested shoreline development may promote higher submersed species richness. However, macrophyte response evaluated at different spatial scales may not be directly comparable given that the effects of stressors could vary depending on site-level or lake-wide effects. Lake-wide effects of shoreline development may induce an overall shift in community characteristics, whereas spatial distribution of macrophytes within the lake may not be homogeneous. For example, lakes with more shoreline development (particularly deep lakes with low watershed development) may have higher species richness, although richness may vary spatially within the lake such that locations farther from docks have more species. Given that macrophyte assemblage composition can vary regionally between lakes as well as spatially within lakes (Moyle, 1945; Mikulyuk et al., 2011), the variable effect of stressors at different spatial scales is not entirely unexpected. Other studies that examined stressor effects at different spatial scales have produced similar results. For example, the abundance of submersed vegetation may be related to stressors from the watershed but not from shoreline areas, whereas emergent and floating-leaf vegetation may be related to both watershed and shoreline development (Jennings et al., 2003). Although Jennings et al. (2003) evaluated abundance rather than richness and shoreline development was measured as residential housing density, the similarity with our results provides further evidence that macrophytes are responsive indicators of human-induced stressors at different spatial scales. Emergent and floating-leaf species appear to be particularly diagnostic of stressors related to shoreline development. However, the synergistic effect of stressors originating at different spatial scales is potentially greater than the individual influence of separate stressors (Mikulyuk et al., 2011). Therefore, conclusions regarding effects of specific stressors should be made in the context of others, in addition to natural variability in community composition.

The specific relationship of total species richness and sensitive species presence/absence with distance to the nearest structure suggests that shoreline development may have extensive and far-reaching effects on littoral habitat. Very few studies have quantified the potential range or distance of influence that shoreline development within lakes may have on aquatic habitat. Radomski et al. (2010) considered areas within a 7.62 m (25 ft) of a dock as potential impact zones around which aquatic habitat is particularly vulnerable to degradation. This buffer distance was based on one-half the median shoreline distance that homeowners are allowed to remove vegetation by permit in Minnesota. The relationships we have shown suggest that this impact zone may be a conservative estimate of the potential effects of shoreline development. Although the confidence intervals in the effects plots are of considerable size, a continuous decline in total species richness and sensitive species presence/absence is observed across the range of distances. Therefore, the impact zone may far exceed 7.62 m, although the most dramatic declines are likely observed closer to a structure. Additionally, the significant interaction of distance to structure with depth indicates that this response may only be relevant for littoral areas at shallow depths (fig. 3.6). This interaction is non-trivial and suggests that littoral habitat in shallow areas on undeveloped shoreline has greater species richness, whereas the opposite may be true for areas near structures. Conversely, richness metrics decline with increasing depth regardless of distance to structure.

3.4.2 Limitations of the data and analyses

Several limitations of our dataset and analyses should be noted. First and most importantly, we have only evaluated the response of macrophyte richness metrics to shoreline development, whereas other metrics could provide additional or more substantial information about macrophyte response. Most studies that have evaluated macrophyte response to shoreline development have examined relative abundance or frequency measurements (e.g., Radomski and Goeman, 2001; Jennings et al., 2003). These metrics may be better indicators of shoreline development because macrophytes removed from shorelines may have the ability to colonize undeveloped areas. Thus, a change in frequency or abundance at the lake-wide scale may be observed in response to shoreline development, whereas total species richness may not indicate an effect. However, our results have shown that littoral areas farther from structures are more likely to have higher species richness. Furthermore, the between-lake analyses indicated a response of richness metrics at the whole-lake scale, which suggests a combined and cumulative impact of site-level alterations could induce community-wide changes. Additional research could examine the precise mechanisms of community degradation at the whole-lake scale as explained by site-level alterations in frequency and abundance, particularly in relation to species richness metrics.

An additional drawback of our study is the limited range of lake types that were used for the within-lake analyses. Although a sufficient number of survey points were available for the analysis, the three lakes do not characterize the range of lake types throughout the state. In particular, these lakes are small and mesotrophic with relatively small, wooded watersheds. Although these lakes were well-suited to evaluate the potential effects of shoreline development (i.e., removal of watershed effects), the results cannot be extrapolated to other lake types. Additionally, very few emergent and floating-leaf species were observed in the study lakes and we were unable to examine the relationship of these species with shoreline development. However, the average dock density for all lakes in the ecoregion is approximately four docks per shoreline kilometer and the study lakes have dock densities approximately three to four times the average (Christmas 15 docks/km, Jane 17 docks/km, Square 12 docks/km). The low frequency occurrence of emergent-floating vegetation may suggest that these species have already been removed from the lakes as a result of development. Finally, the explanatory variables used in the analyses represent a limited set of lake characteristics that influence macrophyte growth patterns. Although depth at each point and distance to the nearest structure explained a significant fraction of variation of the macrophyte metrics, other variables could be used to improve model performance. For example, bottom substrate, wind exposure, and littoral slope influence macrophyte distribution, although these variables are usually not obtained during point intercept surveys.

3.4.3 Conclusions

Our analyses have indicated that shoreline development, using docks as surrogate indicators of stressors, may significantly affect whole-lake macrophyte assemblages and individual sites within lakes. Deeper lakes with low watershed development were particularly vulnerable such that more shoreline development was associated with fewer emergent-floating and sensitive species. Within-lakes, locations in the littoral zone that were farther from docks were more likely to have higher species richness and presence of sensitive species, although these results may only apply to small, mesotrophic lakes with undeveloped watersheds. Overall, these results provide valuable information that supports previous research evaluating the effects of shoreline development on aquatic habitat

(Christensen et al., 1996; Radomski and Goeman, 2001; Jennings et al., 2003; Marburg et al., 2006). More importantly, our results improve understanding of the effects of anthropogenic stressors in nearshore environments as very few studies have examined macrophyte richness response. This suggests that site-level impacts via removal of vegetation may have cumulative lake-wide effects on richness metrics, as well as alter the distribution of species within lakes. Additionally, our between-lake analyses utilized a large dataset that improves confidence in the interpretation of results by illustrating the response of macrophyte assemblages in lakes with a range of limnological characteristics. However, consistent trends in macrophyte response to shoreline development should be interpreted in the context of other stressors, particularly watershed development, which may mask any potential effects of shoreline development at the whole-lake scale.

Table 3.1: Summary of variables used in between-lake analyses for all lakes ($n = 1444$). Response variables for each analysis included total, submersed, emergent-floating, and sensitive species richness. All other variables represent explanatory variables. See section 3.2.1 for variable descriptions.

Variable	Units	Mean (95% CI)	Range
Total	Count	20.5 (20, 21.1)	1, 64
Submersed	Count	10.4 (10.1, 10.7)	0, 29
Emerge/Float	Count	6.6 (6.4, 6.8)	0, 22
Sensitive	Count	2.5 (2.4, 2.7)	0, 15
Dock density	No./shore km	4.5 (4.2, 4.8)	0, 31.2
Surface area	Hectares	210 (187.2, 232.9)	0.9, 6458.1
Max depth	Meters	11 (10.6, 11.5)	0.9, 102.7
TSI	Continuous	52 (51.4, 52.5)	24.6, 90.1
PC1	Continuous	0 (-0.1, 0.1)	-1.8, 2.8

Table 3.2: Summary of variables used in within-lake analyses for all survey points ($n = 1007$) in three lakes. Response variables for each model included richness or presence of total, submersed, and sensitive species. Distance to the nearest dock and depth at each point were used as explanatory variables.

Variable	Units	Mean (95% CI)	Range
Total	Count	2.7 (2.6, 2.8)	0, 11
Submersed	Count	2.3 (2.2, 2.5)	0, 10
Sensitive	Count	0.3 (0.3, 0.4)	0, 2
Distance to dock	m	69.1 (65.7, 72.4)	1.4, 262.8
Depth	m	3.1 (2.9, 3.2)	0, 11.8

Table 3.3: Summary of significant dock density (docks per km of shoreline) variables for GLMs used in between-lake analyses. Significant variables are shown for analyses that evaluated the entire set and stratified subsets of lakes (fig. 3.1). Response variables included total, submersed, emergent/floating, and sensitive species richness. Response variables not shown did not include dock density as a significant explanatory variable. Explanatory variables are shown only if they include main or interactive effects for dock density (dock variable). Full models are shown in tables C.3 to C.7.

Analysis	Response	Dock variable	Estimate	SE	Z	p
All lakes	Total	Area:Dock	-0.03	0.01	-4.56	<0.005
	Total	TSI:Dock	0.00	0.00	3.21	<0.005
	Total	Dock:PC1	0.05	0.01	7.80	<0.005
	Submersed	Dock	0.11	0.03	3.32	<0.005
	Emerge/Float	Dock	-0.05	0.01	-3.43	<0.005
	Emerge/Float	Dock:PC1	0.03	0.01	2.69	0.007
	Sensitive	Dock	0.46	0.23	2.02	0.043
	Sensitive	Depth:Dock	-0.11	0.04	-2.68	0.007
	Sensitive	TSI:Dock	-0.01	0.00	-2.03	0.042
	Sensitive	Dock:PC1	-0.11	0.02	-4.50	<0.005
Shallow, low dev	Total	Dock	0.28	0.05	5.51	<0.005
	Total	Area:Dock	-0.04	0.01	-3.58	<0.005
	Submersed	Dock	0.16	0.08	2.15	0.031
	Emerge/Float	Dock	-0.06	0.02	-3.23	<0.005
	Sensitive	Dock	-0.26	0.03	-8.20	<0.005
Deep, low dev	Total	Dock	0.36	0.08	4.45	<0.005
	Total	Area:Dock	-0.03	0.01	-3.79	<0.005
	Total	TSI:Dock	-0.00	0.00	-2.11	0.034
	Submersed	Dock	0.09	0.01	6.42	<0.005
	Emerge/Float	Dock	-0.05	0.02	-3.12	<0.005
	Sensitive	Dock	-0.33	0.03	-10.86	<0.005
Shallow, high dev	Total	Dock	0.05	0.02	3.04	<0.005
	Submersed	Dock	0.07	0.02	3.18	<0.005
	Emerge/Float	Dock	-0.07	0.03	-2.44	0.015
Deep, high dev	Total	Dock	0.06	0.02	3.02	<0.005
	Emerge/Float	Dock	-0.11	0.03	-3.51	<0.005
	Sensitive	Dock	-0.18	0.09	-2.13	0.033

Table 3.4: Optimal GLMMs for within lake analyses to evaluate effects of shoreline development on macrophyte richness metrics (see fig. 3.2). Response variables were total and submersed species richness and sensitive species presence/absence. Each model included a random intercept for the categorical lake variable (Groups: lake).

	Total	Submersed	Sensitive
(Intercept)	1.22^{***}	-0.55^{***}	-7.57^{***}
	(0.17)	(0.10)	(1.30)
Distance	0.16^{***}	0.03	1.75^{***}
	(0.04)	(0.02)	(0.24)
Depth	-0.41^{**}		4.80^{***}
	(0.16)		(0.66)
Distance:Depth	-0.08^{*}		-1.28^{***}
	(0.04)		(0.17)
AIC	1187.80	294.74	876.03
BIC	1212.37	309.48	900.60
Log Likelihood	-588.90	-144.37	-433.01
Deviance	1177.80	288.74	866.03
Num. obs.	1007	1007	1007
Groups: lake	3	3	3

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

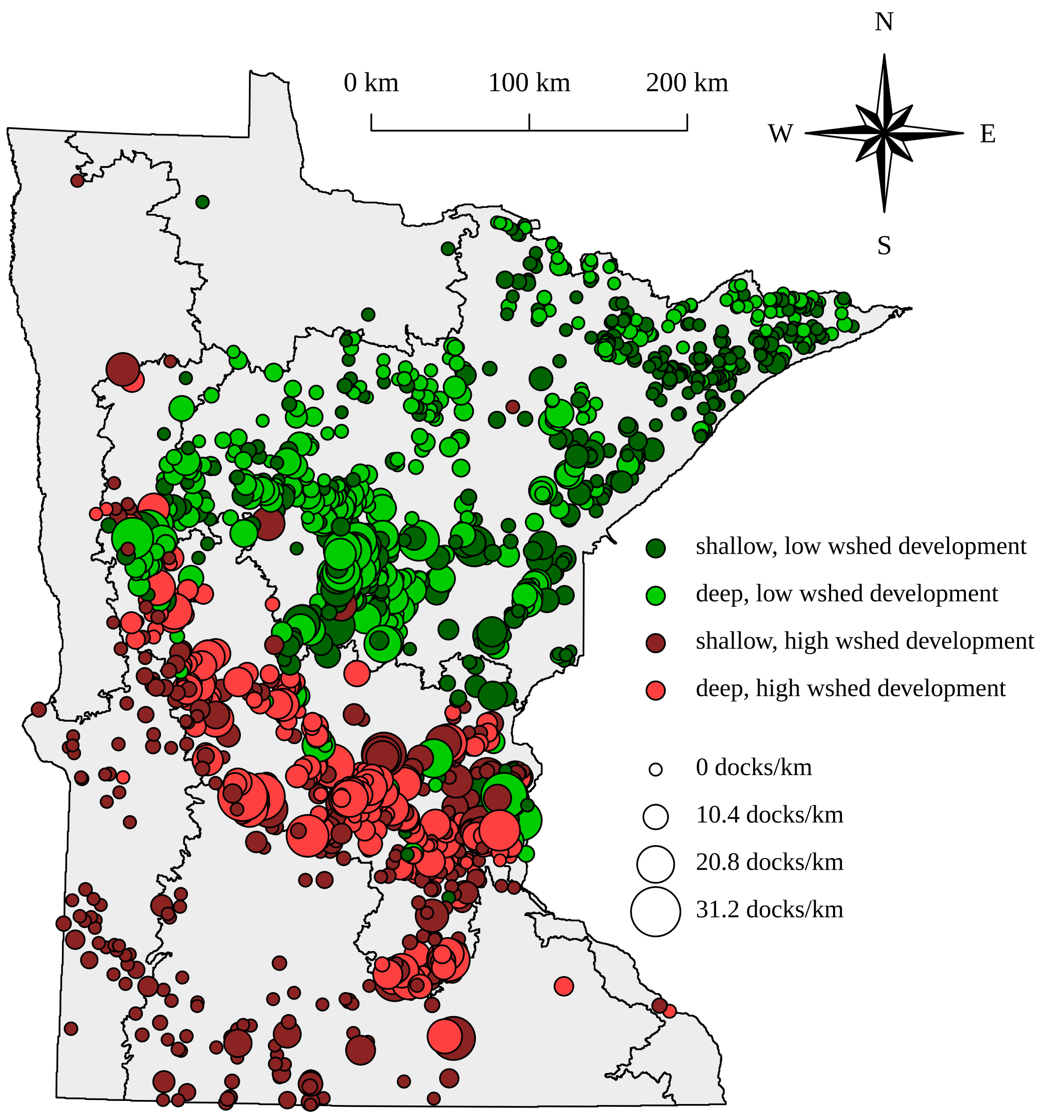


Figure 3.1: Locations of 1444 lakes used to evaluate potential effects of docks between lakes. Lake points are color-coded to indicate lake groups used in the stratified analyses (section 3.2.1): 1) shallow lakes with low watershed development ($n = 439$); 2) deep lakes with low watershed development ($n = 414$); 3) shallow lakes with high watershed development ($n = 352$); and 4) deep lakes with high watershed development ($n = 239$). Point size for each lake represents the estimated dock density (see chapter 2) as a continuous variable from 0 to 31.2 docks per shoreline km.

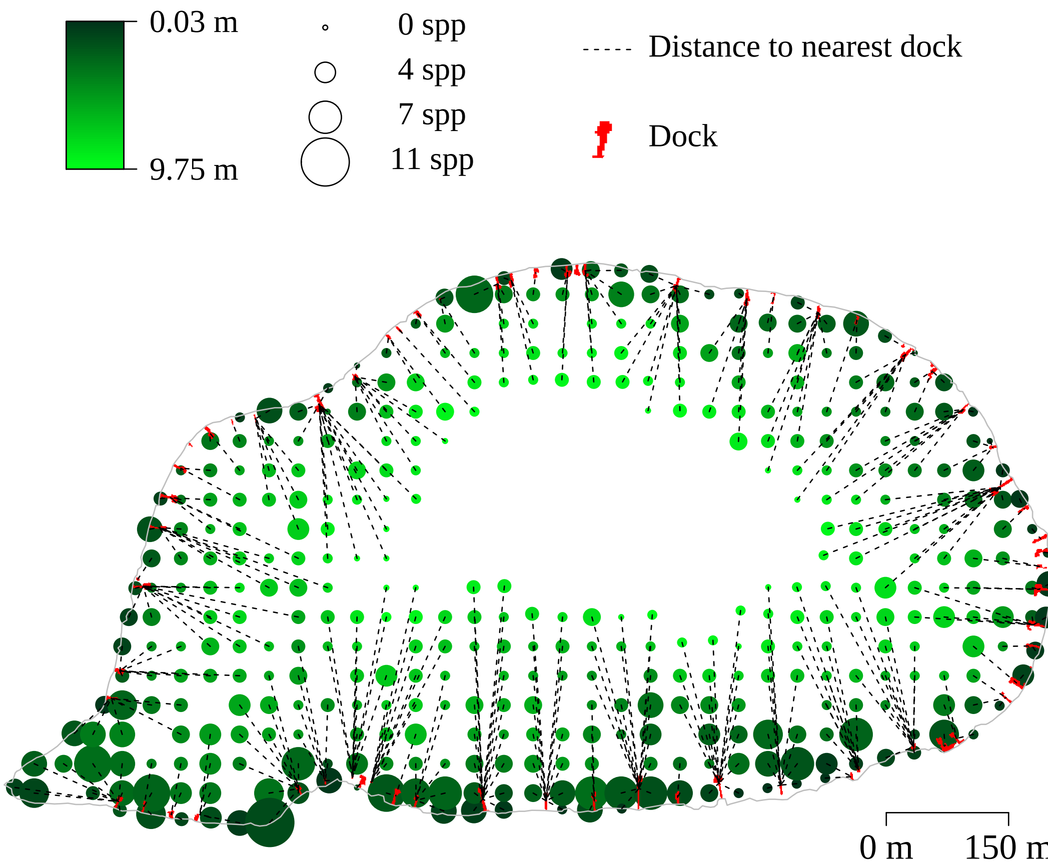


Figure 3.2: Illustration of approach used to evaluate the potential within-lake effects of docks using Jane lake (Washington county). Color of each survey point is proportional to depth and size is proportional to species richness. Dashed lines indicate the distance and direction to the nearest dock for each point.

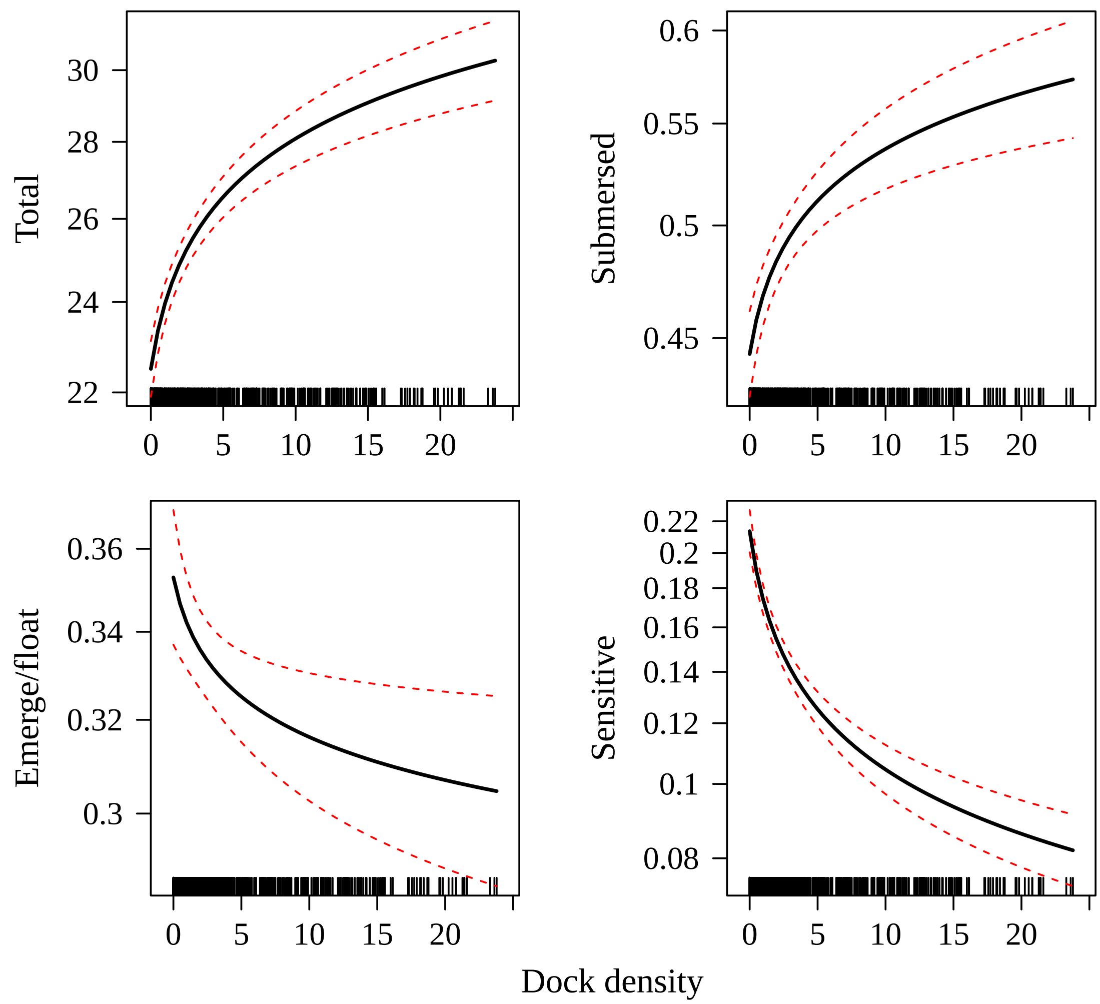


Figure 3.3: Effects plots indicating main effects of dock density (docks per shoreline km) on macrophyte richness metrics for lakes that are deep with low watershed development ($n = 414$). Fitted values were obtained from GLMs describing the effect of dock density on total, submersed, emergent/floating, and sensitive species richness in the context of lake area, TSI, and second-order interactions. All plots except total species richness indicate the proportion of total richness for each group. The rug-plot at the bottom of each figure indicates the marginal distribution of dock density. Dashed lines indicate 95% confidence intervals. Note that the optimal models included significant higher-order interactions for total species richness with other explanatory variables (fig. 3.4).

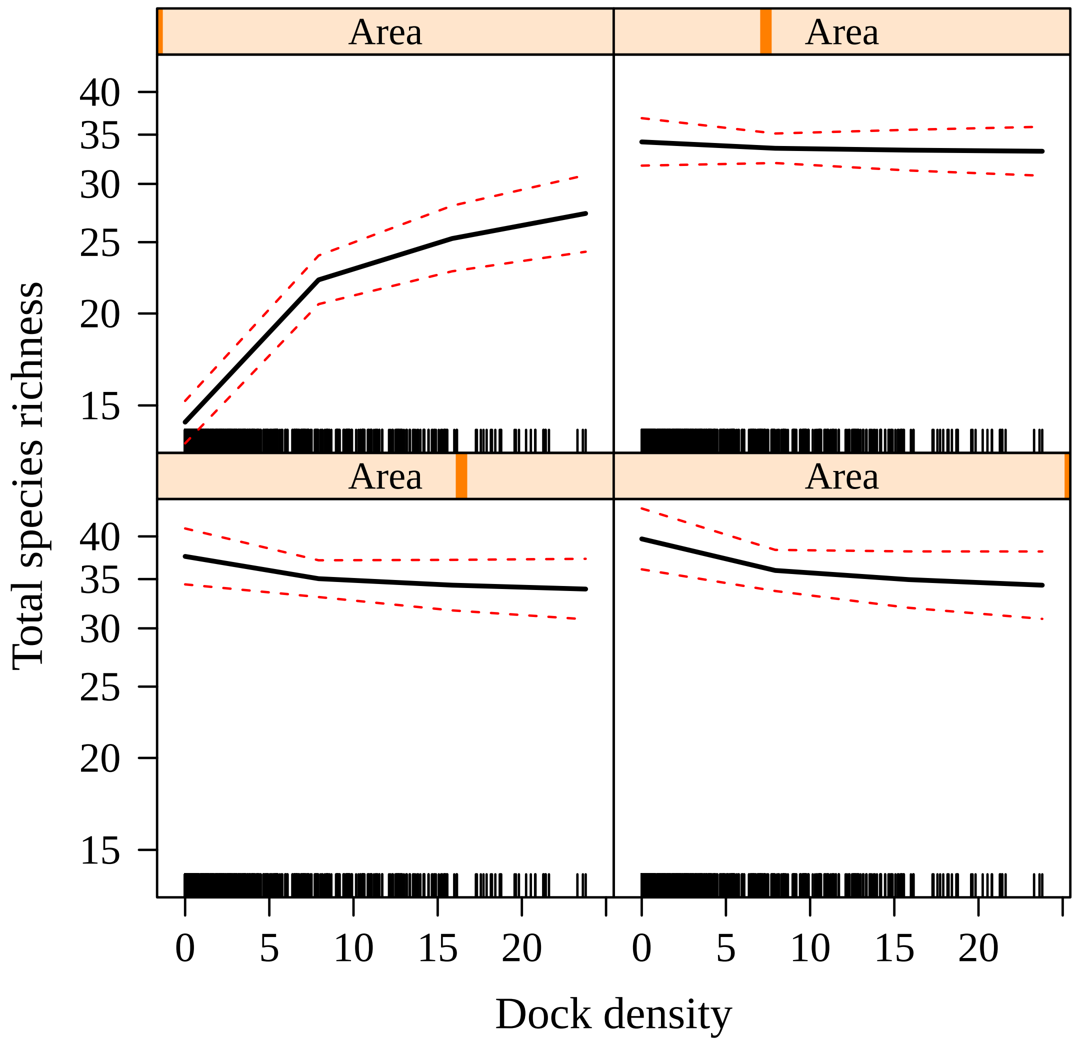


Figure 3.4: Effects plots indicating the interactive effects of dock density (docks per shoreline km) and lake area on total species richness for lakes that are deep with low watershed development ($n = 414$). The rug-plot at the bottom of each figure indicates the marginal distribution of dock density. Vertical orange bars indicate the value at which lake area was held constant to evaluate the effect of dock density, such that lake area increases from top-left to bottom-right. Dashed lines indicate 95% confidence intervals.

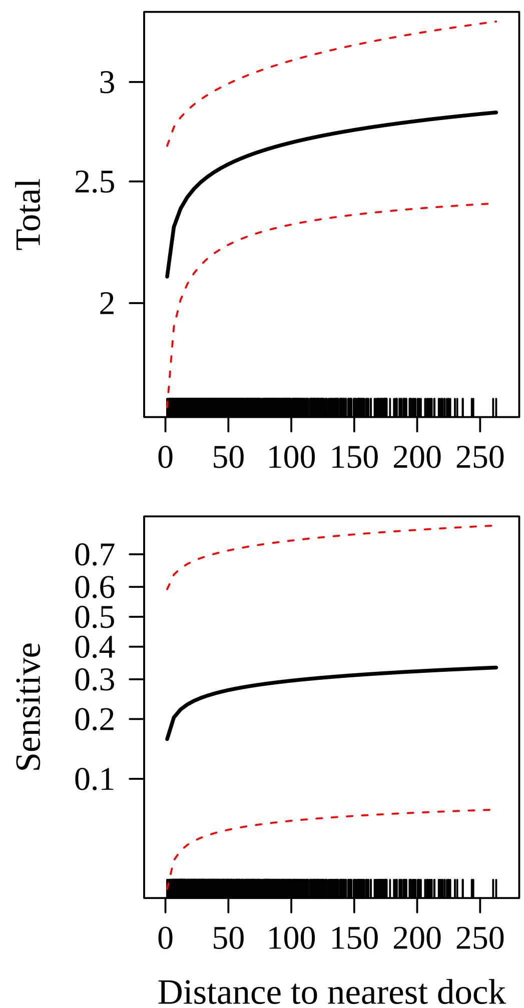


Figure 3.5: Effects plots indicating the main effects of distance to nearest structure (m) on macrophyte metrics for within-lake analyses. Figures represent results from evaluating all survey points ($n = 1007$). Fitted values were obtained from GLMMs describing the effect of distance to nearest structure on total species richness and sensitive species presence/absence (indicated by log-odds). The rug-plot at the bottom of each figure indicates the marginal distribution of distance to nearest structure. Dashed lines indicate 95% confidence intervals. Note that significant interactions between distance to structure and depth were also observed for both response variables (figs. 3.6 and C.1).

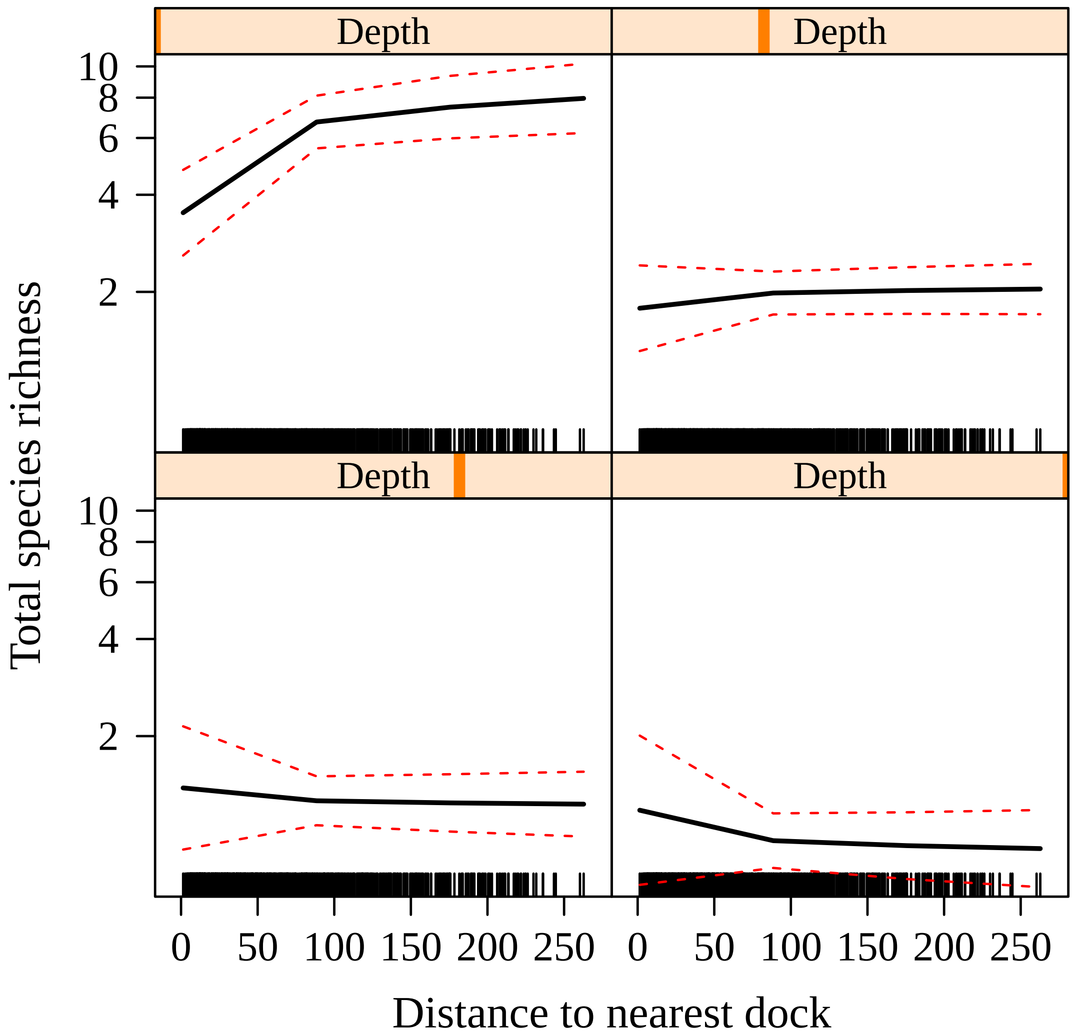


Figure 3.6: Effects plots indicating the interactive effects of distance to nearest structure (m) and depth (m) on total species richness for within-lake analyses. Similar effects were observed for sensitive species (fig. C.1). The rug-plot at the bottom of each figure indicates the marginal distribution of distance to nearest structure. Vertical orange bars indicate the value at which depth at each point was held constant to evaluate the effect of distance to nearest structure, such that point depth increases from top-left to bottom-right. Dashed lines indicate 95% confidence intervals.

Chapter 4

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

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 that affect natural resources can inform their implementation in management. Analytical approaches using supervised neural networks could provide a powerful technique to evaluate IBIs. The objective of this study was to evaluate the use of neural networks to quantify IBI response to environmental condition using an aquatic macrophyte-based IBI developed for Minnesota lakes. Neural networks were expected to illustrate key predictors of IBI performance and provide a general 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 response, suggesting the use of neural networks may be unnecessary if assumptions for conventional models are met. We also suggest that IBIs may inherently confound relationships among variables, rather than an inability of statistical models to characterize variable importance. These results suggest that the statistical properties of multimetric indices should be carefully evaluated during index development, with specific attention given to the sensitivity and diagnostic capabilities of individual metrics.

4.1 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). Legislative mandates under the CWA have been established to restore and maintain the chemical, physical, and biological integrity (Barbour et al., 2000), whereas the WFD seeks to prevent further deterioration of, and protect and enhance the ecological and chemical status of, aquatic ecosystems (Pollard and Huxham, 1998). Both initiatives define conditions of aquatic systems that are beneficial for or supportive of aquatic life that maintain ecological integrity or 'good surface water status' capable of expressing the structure or function of aquatic ecosystems comparable to that of natural habitat for a given 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; Aguiar et al., 2009), 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; Breine et al., 2004), macroinvertebrates (Kerans and Karr, 1994; Barbour et al., 1996), plankton (Lougheed and Chow-Fraser, 2002; Wu et al., 2012), or aquatic vascular plants (Miller et al., 2006; Beck et al., 2010) as biological indicators. IBIs can form the basis of biological standards that identify high-quality systems for protection or degraded systems that require restoration or remediation activities. An IBI relies primarily on the use of 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 adaptation for use in regions with different biological communities. Additionally, Karr and Chu (1999) advocate the IBI as a useful tool for evaluating the complexity of environmental systems by allowing 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). However, Karr and Chu (1999) maintain that overall IBI scores establish a basis for further investigation, such that individual metrics could be used to diagnose specific causes of impairment. More specifically, metrics are not lost in the analysis but rather serve as multiple lines of evidence that increase confidence in evaluation of biotic integrity. 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 based on assumptions under 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. Specifically, models of IBI scores were based on site, year, and sampling effects, rather than an evaluation of metric contributions to understanding the IBI. 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. Obtaining this information may only be possible through the use of multivariate methods that have the flexibility to model data with different or ambiguous distributions.

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; Bishop, 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 determine whether supervised neural networks can provide a useful approach to understand IBI response as a basis for informing index use in biological monitoring. We expect that the methods used to quantify IBI response could be broadly applicable for any multimetric index. We hypothesized that neural networks can illustrate the relationship of IBI scores and individual metrics with key explanatory variables that are related to lake condition. We expect that these relationships can be evaluated in the context of other explanatory variables (i.e., interactions) and non-linear response of IBI variables across different ranges of specific explanatory variables. In particular, neural networks may provide an approach for evaluating diagnostic capabilities of individual metrics that could facilitate the identification of stressors in impaired systems. We describe the application of neural networks to quantify response of a macrophyte-based plant IBI for Minnesota lakes. Lakes in northern and southern groups of a statewide dataset were also evaluated to determine whether regionally-specific IBIs exhibited improved performance. Throughout, performance describes both the ability of neural networks to quantify ecological relationships of IBI scores with explanatory variables and the ability of the IBI to respond to anthropogenic stressors. Methods for quantifying the explicit relationships between explanatory variables and neural network response variables are used to identify diagnostic capabilities of the IBI. Finally, conventional statistical techniques (e.g., linear regression) were used to model IBI scores to determine if neural networks improved predictive performance.

4.2 Methods

4.2.1 Data collection and IBI framework

We used a dataset of 332 lakes obtained from the Minnesota Department of Natural Resources (MNDNR) to evaluate IBIs with neural networks (fig. 4.1). All data were point intercept surveys that provided quantitative and spatially explicit information of macrophyte community composition (Madsen, 1999; Cheruvelil and Soranno, 2008). A grid of survey points spaced at regular distances was created in the littoral area of each lake. Survey points were navigated to by boat with GPS units. Spacing between points was sufficient to capture at least 80% of total species richness in each lake. Macrophytes were sampled at survey points using a double-sided rake attached to a rope. The rake was dropped to the lake bottom at each point to sample an area of approximately 1 m^2. Macrophytes retrieved on the rake were identified to species using Fassett (1957) and Borman et al. (2001). Depth at each point was recorded.

The macrophyte IBI contains seven metrics that quantify attributes or characteristics of macrophyte communities that are meant to respond to environmental changes and was developed with 97 lakes that were included in the current dataset (Beck et al., 2010). Metrics include maximum depth of plant growth at 95% occurrence (MAXD), percentage of littoral vegetated (LITT), number of species with frequency occurrence $> 10\%$ (OVER), relative frequency of submersed species (SUBM), relative frequency of sensitive species (SENS), relative frequency of tolerant species (TOLR), and number of native taxa (TAXA). Metrics were quantified using information from point intercept surveys, scaled continuously from 0–10, and summed to obtain an IBI score for each lake. The original IBI (Beck et al., 2010) was modified for the current analysis to include an additional metric that quantified the relative frequency of emergent and floating-leaf species (EMFL) in each lake. EMFL species may be particularly vulnerable to the effects of residential development on lake shorelines (see chapter 3, Radomski and Goeman, 2001; Jennings et al., 2003).

Neural networks were developed for all 332 lakes. Additionally, models were developed using northern ($n = 145$) and southern ($n = 187$) subsets to determine whether regionally-specific IBIs more effectively characterized lake conditions. Lakes in the Northern Lakes and Forests ecoregion (Omernik, 1987) were included in the northern group, whereas all other lakes were included in the southern group (fig. 4.1). Macrophyte communities vary in composition and tolerance to water chemistry parameters from southern to northern Minnesota (Moyle, 1956). Accordingly, quantification of the effects of anthropogenic stressors on lakes with similar macrophyte communities may be more easily distinguished using IBIs with regionally-specific scoring (see chapter 1). Metrics for each lake group were rescaled from 0–10 using the range of values for the raw metrics (i.e., unscaled) specific to each group, comparable to a reference site approach (Stoddard et al., 2006). Metric scaling within groups allows comparability of IBI scores between regions if raw metrics exhibit substantial geographic variability (Karr et al., 1986; Southerland et al., 2007).

Lake characteristics that could potentially influence IBI performance were also quantified and used as input variables for the neural networks. Characteristics included natural habitat variables and anthropogenic or human-induced stressors. Natural lake characteristics included surface area (*hectares*), maximum lake depth (*depth_m*, meters), mean Growing Degree Days (*GDD*), ratio of watershed area to lake surface area (*wshed_sa*), and a Crop Productivity Index for each lake's watershed (*CPI*). Anthropogenic variables included lake trophic state index (*tsi*), proportion of watershed land use as agriculture (*ag*) or impervious surfaces (*wshed_imperv*, i.e., roads, rooftops), watershed density of groundwater wells (*wshed_well*), and number of docks per km of shoreline (*num_sc*). Watersheds for each lake were identified as all contributing upstream lake catchments, including the immediate lake catchment (MNDNR watersheds level 08; MNDNR, 2012a). Watershed well density was a proxy measure of groundwater withdrawal and was correlated with variable lake levels (unpublished data, shapefile from MnGeo, 2013). See chapters 1 and 3 for a detailed explanation of the remaining variables. All lake characteristics were evaluated for collinearity with Variance Inflation Factors (VIF, Montgomery and Peck, 1992; Zuur et al., 2007). Stepwise comparison of variables indicated all VIFs were less than 10.

4.2.2 Neural network development

Initial research on neural networks began in the 1940s (McCulloch and Pitts, 1943; Pitts and McCulloch, 1947) but their use was not popularized until development of the back-propagation algorithm (Rumelhart et al., 1986). This algorithm provided a computationally-efficient approach for neural networks to 'learn' the inherent relationships among variables using a series of iterative training steps, whereby model weights are successively altered to minimize prediction bias or error. A neural network trained using the back-propagation algorithm has the capacity to approximate any continuous function (Hornik, 1991) and is similar to a non-linear regression model with a sufficiently large number of parameters. Information in the neural network passes between layers composed of neurons or nodes (McCulloch and Pitts, 1943). A typical network has three layers: input, hidden, and output (fig. 4.2a). Input and output layers are analogous to explanatory and response variables in a conventional model. The hidden layer mediates the connections between the two and improves the model's ability to characterize relationships among variables (Hornik, 1991; Lek et al., 2000). Signals progress through nodes in each layer using multiple weighted connections that dictate the relative influence of information. The nodes process information as the summation of values from input nodes, multiplied by the connection weights (fig. 4.2b). An activation function is applied to the weighted information that exits a node, which is then passed to additional neurons or leaves the network. More detailed discussions of the theoretical foundations of neural networks can be found in Bishop (1995) and Ripley (1996).

A trial-and-error approach is typically adopted to develop neural networks since no strict rules are defined for identifying optimal models (Maier and Dandy, 2000). We define 'optimal' as the combination of parameter values (e.g., network architecture, starting weights) that minimizes prediction error during model training, while also predicting values that approximate observed values on an independent dataset not used in training. We used the `nnet` package in program R (RDCT, 2013) to develop the neural networks (Ripley, 1996; Venables and Ripley, 2002). The `nnet` package is used to create a three-layer, feed-forward network that is trained using a variation of the back-propagation algorithm that incorporates weight decay. The decay value imposes a penalty on the weight changes during each training iteration to ensure that the function approximated by the model is smooth (i.e., no 'large' weights). An appropriate decay value also minimizes over-fitting or an inability to generalize predictions on an independent dataset (Ripley, 1996). Additionally, model fit is dependent on the number of nodes in the hidden layer such that too few or too many nodes may induce prediction bias (Maier and Dandy, 2000). For each lake group (all, northern, and southern), we used a systematic approach to identify the optimal combination of decay values and number of nodes in the hidden layer. Specifically, we evaluated all unique combinations of decay values from 0 to 0.01 (Ripley, 1996) and number of nodes from 5 to 15 (Scardi, 2001) using vectors with ten values each, such that 100 combinations were evaluated. Each lake group was separated into a training, validation, and test dataset based on a random 2:1:1 split of lakes in each group (Karul and Soyupak, 2006). Training datasets were used to train the neural networks, validation datasets were used to identify the optimal set of model parameters that minimized prediction error, and test datasets were used as an independent evaluation of model performance.

All models were allowed to progress to 2000 training iterations or convergence on a minimum error for the given parameters, whichever occurred first. Each of the 100 combinations of decay values and number of nodes were evaluated using 100 models that were initiated with a different set of random starting weights from -0.3–0.3. Prediction error is dependent on the initial starting weights that connect the nodes such that a local minimum in the error surface for a given combination of parameters may be obtained rather than the global minimum (Ripley, 1996; Lek et al., 2000). Therefore, 10000 models (100 node/decay combinations $\times$ 100 models with random starting weights) were developed for each of the three IBI lake groups to identify a global error minimum. Neural networks were also developed using IBI scores as a single output node and using the metrics as eight output nodes in the same model. This approach enabled neural networks to characterize multivariate response variables (i.e., metrics) that influence biotic integrity. Therefore, 60000 total models were evaluated: 10000 for IBI scores as output, 10000 for the models with eight outputs for the metrics, and repeated for each of three lake groups.

The optimal set of parameters (decay value, number of hidden nodes, random starting weights) for each lake group and each response variable was identified based on the minimum prediction error for validation datasets. Error was defined as the normalized mean square error (NMSE) between the predicted values from the model and the observed values (Gershenfeld and Weigend, 1993):

$$NMSE = \frac{\sum_{i=1}^{n}(Obs_i - Pred_i)^2}{\sum_{i=1}^{n}(Obs_i - \overline{Obs})^2} \tag{4.1}$$

where $Pred_i$ is a predicted value from the model and Obs_i is the observed or actual value for a response variable from lake i. Normalizing by $Obs_i - \overline{Obs}$ allows comparability of error values for data with different ranges. NMSE values equal to zero indicate absolute precision between predicted and observed values, values equal to one indicate predicted values are equal to the mean of the observed values, and values greater than one indicate predicted values vary greatly from the observed values (Gershenfeld and Weigend, 1993). Errors were determined for each metric and overall IBI scores, such that a unique combination of parameter values that minimized error for each output node of the neural network models was identified.

Explanatory and response variables in each lake group were standardized and rescaled prior to training the neural networks. Explanatory variables were standardized to z-scores such that (using notation in Olden and Jackson, 2002):

$$z_n = \frac{x_n - \bar{x}}{\sigma_x} \tag{4.2}$$

where z_n is the standardized value for observation n, x_n is the observed value for observation n, and $\bar{x}$ and σ_x are the mean and standard deviation of variable x. Standardizing explanatory variables ensures that the weight values determined during model training have equal contribution for explanatory variables with different orders of magnitude (Lek et al., 1996). Response variables were rescaled to 0–1 such that:

$$r_n = \frac{y_n - y_{min}}{y_{max} - y_{min}} \tag{4.3}$$

where r_n is the rescaled value for observation n of response variable y divided by the range of values for y. Rescaling allows use of a logistic activation function for information passed between neurons in the network (Lek et al., 1996; Olden and Jackson, 2002).

4.2.3 Neural network evaluation and indications of variable importance

Predictive performance of the neural networks for each lake group and response variable was evaluated for all datasets (training, validation, and test). However, performance on the test datasets was considered the primary measure of the ability of the models to generalize ecological relationships. NMSE values close to zero indicated excellent model performance, whereas values greater than one indicated poor model performance. The optimal parameters that minimized prediction for overall IBI scores and each metric were also identified.

Several techniques have been developed to interpret neural network weights as a basis for inferring causation, such as neural network interpretation diagrams (Özesmi and Özesmi, 1999), Garson's algorithm (Garson, 1991; Goh, 1995), and Lek's profile method (Lek et al., 1996). These techniques address the criticism that neural networks are a 'black box' approach that provide no information about processes in the modelled system (Benitez et al., 1997; Olden and Jackson, 2002). The optimal models for overall IBI scores and individual metrics were further evaluated using these techniques to describe relationships between explanatory and response variables. Qualitative evaluations were conducted using neural network interpretation diagrams (Özesmi and Özesmi, 1999) that illustrate network architecture based on different shading and colors of connection weights between variables. Quantitative evaluations were conducted using Garson's algorithm (Garson, 1991; Goh, 1995) that identifies the relative importance of explanatory variables (input nodes) on response variables (output nodes) using the weighted connections between layers of a neural network model (Gevrey et al., 2003). The approach identifies all weighted connections between specific input and output nodes that are mediated by the nodes in the hidden layer. The connections are summed for all input nodes and scaled relative to all other inputs to illustrate the relative importance of each explanatory variable. We modified the approach to preserve the sign of the importance values assigned to each variable since Garson's algorithm only indicates relative influence as absolute values.

Preliminary analyses indicated that the neural networks were highly sensitive to the training data. We used a non-parametric bootstrap approach (Efron and Tibshirani, 1993) to evaluate the effects of different training data on information obtained from the models. New training datasets ($n = 1000$) were created for each lake group that were 50% the size of the full datasets using random sampling with replacement. Each random dataset was used to train a neural network model using the network architecture that optimized model performance for each lake group and response variable. Garson's algorithm was used to quantify the relative importance of each explanatory variable for each response variable for the new model. The results were evaluated as mean relative importance values for each explanatory variable with error bars indicating 2.5th and 97.5th quantile values based on results from the 1000 different training datasets. Explanatory variables with error bars that excluded zero were considered ecologically significant for respective response variables (i.e., t-test with $\alpha = 0.05$).

Individual explanatory variables with error bars that did not include zero were further evaluated using a modified version of Lek's profile method (Lek et al., 1996; Gevrey et al., 2003) to determine the explicit form of the relationship with response variables. Lek's profile method plots the expected values from a trained neural network for a response variable across the range of values for a specific explanatory variable. All other explanatory variables are held constant (e.g., minimum, 20th quantile, maximum). We modified Lek's profile method to use constant values for unevaluated explanatory variables based on an agglomerative clustering technique to identify groups of lakes with similar characteristics (Lance and Williams, 1967; Milligan, 1989). This approach provided a more ecologically robust method of evaluating response curves because values for other explanatory variables that were more likely to co-occur across the landscape were identified. The original method maintains other explanatory values at the same value (e.g., maximum) and creates unrealistic response curves because not all lakes are, for example, large, deep, or productive with extensive agricultural land use in their watersheds. We used flexible beta classification to identify six lake groups specific to each evaluated response variable based on dissimilarity measures (Euclidean distance) determined from differences between lakes using all other explanatory variables. Unevaluated explanatory variables were held constant at the mean value for each lake group to determine the response of IBI scores or metrics to specific explanatory variables. This approach was repeated for all significant relationships between variables.

4.2.4 Comparison of neural networks with conventional models

The ability of conventional models to evaluate the IBI was examined to determine whether model type was a significant factor influencing prediction. Conventional models included Multiple Linear Regression (MLR), MLR with stepwise variable selection, Generalized Additive Models (GAM), regression trees, and regression trees with a parameter for optimizing tree complexity. These methods were chosen to provide a balance between linear and non-linear approaches and to determine whether methods based on parsimony (i.e., identification of optimal models with minimal complexity) could improve predictive capabilities. Backward stepwise variable selection with MLR models involved sequential dropping of terms and model comparison using Akaike's Information Criterion (AIC; Akaike, 1973). GAM models were developed using generalised cross-validation and cubic regression splines to identify the optimal smoothing function for each predictor variable (Zuur, 2012). Regression tree models were developed using recursive partitioning of the response variable based on sequential splits of explanatory variables that maximized between-group variation (Zuur et al., 2007). The first group of tree models used maximum recursive partitioning, whereas the second group used models with optimal levels of complexity. The latter approach used a complexity parameter similar to AIC that maximized explained deviance while imposing a penalty for tree size.

Models were developed using IBI scores as a single response variable since the conventional models cannot simultaneously evaluate multiple metrics. All model comparisons used the same training, validation, and test data for each lake group. All models were developed using raw data, rather than the standardized and rescaled data used with neural network models. Model comparisons were identical to the evaluation of neural networks such that error was defined as the NMSE of predictionma. Program R (RDCT, 2013) was used for all analyses using packages `stats` (Venables and Ripley, 2002), `mgcv` (Hastie and Tibshirani, 1990), and `rpart` (Breiman et al., 1984).

4.3 Results

4.3.1 Trends in biotic integrity and model performance

IBI and metric scores varied for all lakes and the northern and southern lake groups. In general, IBI scores varied from southern to northern Minnesota with scores increasing with latitude (Spearman $\rho = 0.65$, $p < 0.005$). Accordingly, separation of lakes into northern and southern groups and rescaling of metrics based on best observable conditions in each group removed the correlation of IBI scores with latitude for the northern group and reduced the correlation for the southern group ($\rho = 0.34$, $p < 0.005$). All metrics for all lakes were positively correlated with latitude. Most notably, TAXA ($\rho = 0.57$, $p < 0.005$) and SENS ($\rho = 0.56$, $p < 0.005$) exhibited the strongest correlations such that species richness and relative frequency of sensitive species increased in northern lakes. Only OVER ($\rho = -0.23$, $p = 0.006$) and TOLR ($\rho = 0.44$, $p < 0.005$) were correlated with latitude in the northern dataset, whereas all metrics except SUBM were positively correlated with latitude in the southern dataset. Explanatory variables also varied spatially across Minnesota. Lakes generally decreased in productivity with increasing latitude such that northern lakes were significantly deeper ($t = 6.05$, $df = 236.59$, $p < 0.005$) and had lower trophic state ($t = -14.59$, $df = 316.69$, $p < 0.005$). See chapters 1 and 3 for a more detailed explanation of statewide variation in lake characteristics.

The range of values for response and explanatory variables for the training, validation, and test datasets in each lake group were similar based on visual assessment of distributions with boxplots. The node and decay combinations that minimized error on the validation datasets varied for each lake group (table 4.1 and figs. 4.3 and 4.4). In particular, no consistent node or decay combinations were observed for neural network models such that the optimum combination differed for each response variable. Mean NMSE values of prediction from the models for all combined lake groups (all, northern, and southern) were 0.330 for the training datasets, 0.635 for the validation datasets, and 1.048 for the test datasets. Mean NMSE values for all combined datasets (training, validation, and test) were 0.568 for all lakes, 0.708 for northern lakes, and 0.736 for southern lakes. Additionally, the performance of models developed using IBI scores as a single response variable (fig. 4.3) was slightly improved over models developed using eight output nodes for each metric (fig. 4.4), although performance varied by dataset and lake group. Mean NMSE values for IBI only models was 0.618, whereas mean NMSE for metric models was 0.678.

Neural network performance using the test datasets indicated that models using all lakes had better performance than those for the northern and southern groups (table 4.1). For all lakes, NMSE values for the trained models using the test dataset were less than one, with the exception of the SENS metric. Prediction errors averaged 0.780 with values ranging from 0.321 to 1.087. For the northern group, models for MAXD, EMFL, SUBM, and TOLR had NMSE values less than one, whereas all other response variables had poor performance. Prediction errors averaged 1.099 with values ranging from 0.734 to 1.535. For the southern group, only models for OVER and TAXA had NMSE values less than one. Prediction errors averaged 1.265 with values ranging from 0.641 to 1.994. The best performing model for all lakes was for TAXA (NMSE 0.321, fig. 4.4a), for northern lakes was MAXD (NMSE 0.734, fig. 4.4b), and for southern lakes was TAXA (NMSE 0.641, fig. 4.4c). Overall, neural network performance was poor, although some models produced robust predictions (e.g., TAXA model for all lakes).

4.3.2 Indications of variable importance

A majority of the relative importance values were not significant based on Garson's algorithm and bootstrap analyses for neural network models of IBI scores (table 4.2 and fig. 4.5). Only *tsi* for all lakes (fig. 4.5b) and *wshed_well* for southern lakes (fig. 4.5f) were significantly different from zero, with IBI scores negatively related to these variables. IBI scores were weakly and negatively associated with *wshed_imperv* and *CPI* (fig. 4.5b) for all lakes, i.e., relative importance was marginally different from zero. No variables were consistently related to IBI scores in the northern group (fig. 4.5d). Results of bootstrap analyses of neural network models for the eight metrics were similar (table 4.3). Only eight of the 240 relationships characterized by the models for all lake groups had confidence intervals that were different from zero. For all lakes, *tsi* was negatively related to MAXD, LITT, OVER, and TAXA and *hectares* was positively related to TAXA. For northern lakes, *tsi* was negatively related to TOLR. For southern lakes, *tsi* was negatively related to OVER and TAXA.

Explicit relationships of explanatory variables that were consistently related to IBI or metric scores were identified using our modified version of Lek's profile method (figs. 4.6, 4.7 and D.1 to D.3). The response of output variables in the neural networks varied depending on lake clusters defined using flexible beta classification. For example, fig. 4.6a indicates that IBI scores in lake cluster six decreased across *tsi* values from 30–50, whereas IBI scores in lake cluster two decreased across *tsi* values from 50–90. Additionally, lake cluster one showed declines in IBI scores across the entire range of *tsi*. Similarly, IBI scores for southern lakes showed different responses to changes in *wshed_well* depending on lake cluster (fig. 4.6b). Most lake clusters had decreasing IBI scores with increasing watershed well density, although the reductions were less than those observed for *tsi* in fig. 4.6a. Metric responses were also consistent with expected relationships of lake characteristics with biotic integrity. For example, fig. 4.7 shows a general increase in species richness (TAXA) with lake size (*hectares*) and a decrease in maximum depth of plant growth (MAXD) with lake trophic state (*tsi*) for all lakes, with relationships varying by lake cluster. The relationships of other metrics and explanatory variables that were consistent in table 4.3 are shown in figs. D.1 to D.3.

4.3.3 Comparison of neural networks with conventional models

Predictions of IBI scores using conventional models were, overall, slightly less precise than those from neural networks (table 4.4). Neural network models for each training dataset, regardless of lake group, indicated higher performance than all other methods. All models for the entire lake group had prediction errors less than null values except the validation dataset using GAMs. Models for the northern and southern lake groups had comparable performance for the training, validation, and test datasets. However, both MLR approaches performed better than all other models (conventional and neural networks) for the test datasets in the northern and southern groups (tables 4.4 and D.1). Additionally, GAMs had better performance for the test dataset in southern lakes than the neural network and regression tree models (tables 4.4 and D.2). Insufficient sample size prevented use of GAMs for the northern dataset. Regression tree models had comparable performance to the other model types (table 4.4 and figs. D.4 and D.5). Regression trees developed using complexity parameters for the entire dataset showed marginal improvement in the validation and test datasets.

4.4 Discussion

An IBI is a tool for researchers and resource managers to interpret complex biological systems using a single numeric value to rank relative site quality. Individual metrics provide information about an aspect of the structure or function of the system that responds to environmental changes. However, few studies that have focused on the development of multimetric indices have performed analyses that evaluate metric and IBI scores in a multivariate context. An understanding of IBI performance, in addition to the identification of environmental characteristics that affect metrics, is critical for informing practical use of an index. Common methods for developing multimetric indices evaluate metric response to environmental stressor gradients as a basis for inclusion in an IBI (Whittier et al., 2007). We suggest that these methods are appropriate, but not sufficient, for assuming an IBI will be diagnostic of key environmental stressors. Specifically, simple bivariate correlations of metrics with environmental stressors may not provide an accurate depiction of metric influences on IBI performance when multiple metrics are combined to obtain overall index scores. Metrics may describe random variables with different underlying distributions and the effect of their combination on biotic integrity is difficult to determine. IBIs are also numerically complex such that a single IBI score may be obtained through multiple combinations of different metrics. For example, an IBI with twelve metrics, each scored as one, three, or five, can produce an overall score of thirty-six with over seventy-thousand different metric combinations (M. Beck, unpublished data). Accordingly, the assumption that metrics can be used to diagnose causes of biological impairment requires robust quantitative techniques to empirically describe index performance.

Our analyses applied supervised neural networks to assess the ability of the index and its metrics to diagnose particular stressors or other explanatory variables. Accordingly, our analyses were meant to inform use of multimetric indices in the management of aquatic systems using a multivariate approach that accommodated the challenges of interpreting multimetric indices. We have shown that neural networks can be used to characterize relationships of IBI scores and individual metrics with environmental variables, although neural network performance is dependent on the training data and populations evaluated. Consistent relationships between IBI and metric scores were observed with a limited number of lake characteristics after re-evaluating indications of variable importance with bootstrap analyses. Key distinctions in model performance were also apparent when evaluating neural networks developed for the different lake groups. Models developed for all lakes had better performance than models developed for the northern or southern groups. Lastly, a comparison of conventional statistical models with neural networks to predict overall IBI scores indicated that neural networks could provide comparable predictions of index performance. Overall, we have shown that neural networks offer a unique approach with key strengths and weaknesses in understanding the complex relationships that influence biotic integrity.

4.4.1 Utility of neural networks to quantify determinants of biotic integrity

Our modifications to Garson's algorithm (Garson, 1991; Goh, 1995) and Lek's profile method (Lek et al., 1996; Gevrey et al., 2003) provided a technique to characterize the relationships quantified by the neural networks. An essential component of these analyses was the use of a non-parametric bootstrap approach to quantify uncertainty in these relationships. Re-sampling of the lake groups to produce different training datasets illustrated that the neural networks were highly sensitive to the data used during model training. The sensitivity of neural networks to training data can reduce the model's potential to predict useful information on an independent dataset. Maier and Dandy (2000) stress the potential bias of neural networks to identify information in training datasets that are not unique to the population of interest. Our initial attempts to ensure that the training datasets were similar to the validation and test datasets involved visual comparisons of variables between datasets using boxplots. However, our use of bootstrap analyses to retrain the neural networks indicated that visual comparisons were insufficient to control for differences between datasets. Accordingly, we recommend that the sensitivity of neural networks to different training datasets be evaluated with quantitative approaches prior to inferring causation among variables. The hold-out method (Maier and Dandy, 2000; Venables and Ripley, 2002) is an additional approach that could be used to train neural networks. This approach trains and averages models using the entire dataset, excluding individual observations during separate training iterations, until the model is trained by sequentially excluding every observation. The approach has been suggested for datasets of limited size, and could be useful for further evaluating IBI performance.

A primary concern with our use of neural networks is the limited sample size, particularly for the northern and southern lake groups. Although neural networks can potentially approximate any smooth function, the number of model parameters (i.e.

connection weights) requires excessive degrees of freedom. For example, a neural network with ten input nodes, ten hidden nodes, and a single response node requires estimation of 121 weights (including bias layers). For a multiple regression model with the same variables that includes second-order interactions, 56 parameters are estimated. Only 11 parameters are estimated if interactions are excluded. Accordingly, the computational advantages of neural networks may be compromised by the requirement for large sample sizes. Sample sizes should be sufficiently large for the model to characterize relationships in the training dataset. Hammerstrom (1993) suggests at least five to ten observations for each connection weight, such that a neural network with 121 connection weights would require a minimum sample size of 605 training observations. Our sample sizes were smaller than the recommended, particularly for models with output nodes for each metric and the northern and southern lake groups. However, an independent evaluation of neural networks to model a fish-based IBI for warmwater streams in Minnesota (Niemela and Feist, 2000, 2002) suggested that sample size, although important, may not have been the primary factor influencing our results. Neural networks were developed for 1173 sites to model IBI scores at individual stream reaches (appendix E). Although the stream and lake IBIs are not ecologically comparable, similar predictive performance was observed between the datasets despite differences in sample size.

Our use of bootstrap analyses provided a useful approach to characterize the uncertainty of relationships described by the neural networks. This approach may have particular merit if sample size is a limiting factor. For example, the analyses indicated that consistent relationships were observed between a limited set of variables, particularly the effects of lake trophic state (*tsi*) on metrics and IBI scores. These trends reflect relationships between lake productivity and macrophyte communities with ecological significance. Specifically, lake phosphorus concentration is a primary driver of lake productivity (Cross and Jacobson, 2013), with associated changes in water clarity and nutrient availability in the water column. Increase in phytoplankton production reduces water clarity and has implications for the diversity and stability of macrophyte communities (Scheffer et al., 1993). Neural networks consistently identified these relationships after evaluations of uncertainty, suggesting our methods provided a viable approach to developing neural networks with small sample sizes. However, the extent to which the neural networks could identify additional relationships with increasing sample sizes remains uncertain. Moreover, the comparison of conventional statistical models with neural networks produced similar results, even though conventional approaches were not as constrained by sample size. This observation provides evidence that sample size may not have been a primary limitation in our analyses.

A common disadvantage of applying neural networks is a lack of approaches for variable selection. Although we attempted to reduce the number of explanatory variables by eliminating collinear inputs with VIF selection and choosing variables with the greatest hypothesized effect on macrophyte communities, the optimal neural network models included parameter estimates for all variables. Techniques for variable selection in multivariate models seek to identify explanatory variables that have the strongest relationships with the response variables, while eliminating those that are redundant or less informative (Akaike, 1973; Zuur et al., 2007). Removing insignificant variables improves model performance by increasing the precision of parameter estimates. Our evaluation of conventional modeling techniques considered models with and without variable selection techniques. In most cases, models that used variable selection improved performance for the test dataset, whereas predictive performance on the training datasets was reduced. The improvement in performance represents a fundamental concept in model development, whereby the optimal model represents a bias-variance tradeoff such that the model has sufficient ability to generalize results to independent datasets. Olden and Jackson (2002) suggested a randomization approach similar to our bootstrap analyses to identify and remove null connection weights between nodes in a neural network. Accordingly, our approach for the randomization of training data is somewhat comparable, such that variables with inconsistent relationships with response variables could be considered insignificant. Predictive performance of the models may be improved by excluding these variables from model training, in addition to a more rigorous application of methods in Olden and Jackson (2002).

Our modification of Lek's profile method (Lek et al., 1996) provided an additional approach to evaluate relationships among variables that have ecological relevance for aquatic systems in Minnesota. A more confident interpretation of ecological relationships between variables was made by approximating values of explanatory variables for lake clusters that resembled natural groupings on the landscape. For example, the functional response of IBI scores with changes in lake productivity (*tsi*) differed depending on the lake cluster evaluated. Two clusters indicated potential thresholds beyond which changes in IBI scores with lake productivity were negligible. For example, IBI scores for cluster two are insensitive to increases in trophic state from oligotrophic to mesotrophic, whereas cluster six is insensitive to changes from mesotrophic to eutrophic (fig. 4.6a). These differences in response are likely related to differences in mean values of the other explanatory variables for the clusters. Most notably, lakes in cluster six were larger with watersheds dominated by urban land use. Macrophyte community integrity may be more affected by other variables at higher *tsi* values in these lakes. Moreover, maximum depth of plant growth for lakes in cluster six is strongly affected by changes in productivity for low *tsi* values, but insensitive across all other values (fig. 4.7b). The effects of lake size and urban land use complicates use of the IBI to diagnose effects of eutrophication. Macrophyte community response to changes in lake characteristics is complex and the ability to visualize these changes is facilitated by our modification of Lek's profile method.

4.4.2 Conclusions

Our analyses suggested that neural networks could identify only a limited set of relationships for the IBI and component metrics with the explanatory variables. Consistent relationships between variables were not unexpected given the known relationships between lake productivity and characteristics of macrophyte communities, such as species richness and maximum depth of plant growth (e.g., Radomski and Perleberg, 2012; Søndergaard et al., 2013). Additionally, our analyses indicated that models developed for the northern and southern lake groups had poor performance relative to models for all lakes. The extent to which limited sample size affected the results for these groups remains unclear. Although increasing sample size may improve model performance, other factors could have contributed to the observed results. In particular, gradients in anthropogenic stress may not be as pronounced for groups of lakes relative to all 332 lakes. A critical aspect of an adequate biological indicator is a sufficient range of response across anthropogenic stress gradients (Whittier et al., 2007). Lack of a gradient may prevent the identification of metrics that respond to changes in environmental condition. As such, primary gradients in lake productivity related to land use are most pronounced from southern to northern Minnesota. Reduction of this stressor gradient within the northern and southern lake groups may have limited the diagnostic capabilities of the IBI. Similar results were observed in chapter 1. Regionally-specific IBIs may only be useful if aquatic communities exhibit sufficient variability related to stressors within a region.

Finally, our analyses suggest that the IBI framework for evaluating biotic integrity may have caused the observed results, rather than an inability of neural networks to describe relationships among variables. Most importantly, our comparison of the neural network method with conventional models indicated that neural networks provided slight, and potentially inconsequential, improvements in explaining IBI scores. Similar predictive performance for different statistical models provides evidence that an IBI may be an insufficient indicator of the effects of multiple stressors on environmental condition. Although standard techniques were used to develop the macrophyte-based IBI (Beck et al., 2010), these methods may unnecessarily complicate the interpretation of biological response. In particular, an IBI is numerically complex and uses an additive combination of variables to characterize biological response to environmental condition. Although the statistical properties of IBIs have been previously investigated (Fore et al., 1994; Dolph et al., 2010), our results provide an incentive for researchers to more thoroughly assess the statistical characteristics of multimetric indices. Evaluations of the multivariate characteristics of metrics prior to inclusion in an IBI may provide the most appropriate means to develop a powerful diagnostic tool that will inform resource management. Clear understanding of the statistical distributions of individual metrics, ensuring minimal redundancy among metrics, and understanding the multivariate distribution of the IBI may provide the best approach to developing an index that is both biologically and statistically sound.

Table 4.1: Error values for the training, validation, and test datasets, for each lake group. Errors are the normalized mean square errors of predicted values for the optimal models. Values in bold italics are prediction errors greater than one, indicating poor model performance. Node, decay, and seed values that minimized error on the validation datasets are shown. Seed values indicate the random number seed for generating starting weights.

					Dataset error		
Group	Variable	Seed	Decay	Node	Training	Validation	Test
	IBI[a]	1093	0.010	11	0.151	0.386	0.442
	MAXD	4214	0.010	8	0.313	0.482	0.642
	LITT	4282	0.010	6	0.545	0.607	0.832
	OVER	1754	0.004	12	0.334	0.467	0.777
All	EMFL	3015	0.007	9	0.260	0.847	0.973
	SUBM	2226	0.000	5	0.611	0.884	0.970
	SENS	3858	0.003	7	0.259	0.567	***1.087***
	TOLR	4950	0.004	6	0.625	0.614	0.975
	TAXA	1864	0.007	14	0.160	0.213	0.321
	IBI[a]	2087	0.003	7	0.163	***1.050***	***1.515***
	MAXD	1624	0.007	15	0.122	0.380	0.734
	LITT	2347	0.001	5	0.572	0.736	***1.205***
	OVER	2348	0.002	7	0.361	0.838	***1.535***
Northern	EMFL	4710	0.007	5	0.459	0.627	0.774
	SUBM	4710	0.007	5	0.497	0.618	0.864
	SENS	1526	0.009	7	0.365	0.753	***1.222***
	TOLR	3427	0.009	15	0.193	0.577	0.830
	TAXA	714	0.003	12	0.354	0.566	***1.214***
	IBI[a]	1886	0.010	6	0.190	0.533	***1.138***
	MAXD	60	0.003	11	0.469	0.431	***1.250***
	LITT	4769	0.006	9	0.233	0.938	***1.026***
	OVER	4284	0.010	9	0.252	0.534	0.930
Southern	EMFL	1672	0.003	7	0.334	0.880	***1.994***
	SUBM	1672	0.003	7	0.349	***1.062***	***1.949***
	SENS	3401	0.010	12	0.175	0.569	***1.120***
	TOLR	832	0.008	11	0.340	0.665	***1.334***
	TAXA	689	0.004	12	0.224	0.325	0.641

[a]Neural networks using IBI scores as single output node.

Table 4.2: Results of bootstrap analyses to quantify variability associated with relative importance of each explanatory variable for IBI scores. Values indicate mean relative importance for 1000 random samples (2.5th and 97.5th percentile values in parentheses) of the training data and the optimal neural network model for each lake group using a single output node for IBI scores. Mean relative importance values in bold italics indicate explanatory variables where the confidence intervals did not include zero. Relative importance was determined using a modification of Garson's algorithm (Garson, 1991; Goh, 1995).

Group	Variable	IBI relative importance
All	hectares	0.05 (-0.55, 0.77)
	depth_m	0.14 (-0.39, 0.91)
	tsi	***-0.91 (-1.00, -0.33)***
	GDD	-0.24 (-0.97, 0.20)
	ag	-0.29 (-1.00, 0.21)
	wshed_imperv	-0.44 (-1.00, 0.04)
	wshed_well	-0.30 (-1.00, 0.27)
	wshed_sa	0.37 (-0.19, 1.00)
	CPI	-0.35 (-1.00, 0.04)
	num_sc	-0.08 (-0.53, 0.31)
Northern	hectares	-0.06 (-0.92, 0.69)
	depth_m	-0.18 (-1.00, 0.54)
	tsi	-0.20 (-1.00, 0.48)
	GDD	-0.10 (-0.85, 0.63)
	ag	0.22 (-0.80, 1.00)
	wshed_imperv	0.04 (-0.72, 0.94)
	wshed_well	-0.77 (-1.00, 0.17)
	wshed_sa	0.24 (-0.80, 1.00)
	CPI	-0.01 (-0.70, 0.71)
	num_sc	-0.18 (-1.00, 0.40)
Southern	hectares	-0.02 (-0.77, 0.71)
	depth_m	-0.18 (-1.00, 0.55)
	tsi	-0.17 (-0.79, 0.41)
	GDD	-0.06 (-0.72, 0.60)
	ag	0.13 (-0.67, 1.00)
	wshed_imperv	0.11 (-0.54, 0.95)
	wshed_well	***-0.85 (-1.00, 0.00)***
	wshed_sa	0.25 (-0.71, 1.00)
	CPI	-0.07 (-0.57, 0.62)
	num_sc	-0.28 (-1.00, 0.17)

Table 4.3: Results of bootstrap analyses to quantify variability associated with relative importance of each explanatory variable for individual metrics. Values indicate mean relative importance for 1000 random samples of the training data and the optimal neural network model for each dataset and metric. Mean relative importance values in bold italics indicate explanatory variables where the 2.5th and 97.5th percentile values (not shown) from the bootstrap analyses did not include zero. Relative importance was determined using a modification of Garson's algorithm (Garson, 1991; Goh, 1995).

		Metric relative importance							
Group	Variable	MAXD	LITT	OVER	EMFL	SUBM	SENS	TOLR	TAXA
All	hectares	0.17	0.07	-0.15	-0.19	-0.09	-0.01	0.02	***0.73***
	depth_m	0.48	0.08	0.13	0.04	0.01	-0.19	-0.21	0.46
	tsi	***-0.74***	***-0.86***	***-0.75***	-0.01	0.02	-0.39	-0.45	***-0.69***
	GDD	0.19	0.23	0.23	-0.21	-0.13	-0.37	-0.56	-0.06
	ag	-0.08	-0.19	-0.29	-0.14	-0.16	-0.22	0.14	-0.36
	wshed_imperv	0.44	0.30	0.02	-0.62	-0.41	-0.38	-0.61	-0.13
	wshed_well	0.01	-0.19	-0.28	0.02	-0.17	-0.20	-0.12	-0.26
	wshed_sa	-0.12	0.28	0.51	0.40	0.27	0.17	-0.03	0.41
	CPI	-0.01	-0.31	-0.28	-0.10	-0.13	-0.20	0.06	-0.25
	num_sc	0.37	-0.07	-0.12	-0.15	-0.20	-0.04	-0.05	0.21
Northern	hectares	0.06	-0.18	-0.29	-0.01	-0.03	0.04	-0.01	0.64
	depth_m	0.41	-0.03	-0.02	-0.24	-0.19	-0.49	-0.32	0.29
	tsi	-0.61	-0.11	-0.09	0.25	0.36	0.00	***-0.64***	-0.15
	GDD	0.37	0.33	0.28	-0.27	-0.20	-0.25	-0.47	0.08
	ag	-0.01	0.05	0.09	0.11	0.13	0.01	-0.03	-0.14
	wshed_imperv	0.34	0.11	0.26	-0.28	-0.24	-0.08	-0.34	0.32
	wshed_well	0.40	-0.22	-0.37	-0.60	-0.57	-0.57	-0.15	-0.41
	wshed_sa	-0.14	0.42	0.54	0.19	0.27	0.14	-0.61	0.32
	CPI	0.23	-0.13	-0.16	-0.18	-0.19	-0.10	0.19	-0.03
	num_sc	0.44	-0.20	-0.05	-0.46	-0.41	-0.09	-0.34	0.28
Southern	hectares	0.18	0.15	0.21	-0.01	-0.01	0.38	-0.11	0.61
	depth_m	0.52	0.16	0.24	0.21	0.21	0.15	-0.38	0.36
	tsi	-0.52	-0.69	***-0.87***	-0.06	-0.01	-0.42	-0.14	***-0.63***
	GDD	-0.10	-0.07	-0.02	-0.14	-0.07	-0.22	-0.43	0.00
	ag	-0.05	-0.14	-0.34	-0.27	-0.27	-0.48	0.19	-0.42
	wshed_imperv	0.34	0.00	-0.14	-0.52	-0.47	-0.16	-0.53	-0.19
	wshed_well	-0.19	-0.18	-0.17	0.20	0.20	0.04	-0.11	-0.22
	wshed_sa	-0.12	0.09	0.33	0.26	0.34	0.09	-0.11	0.37
	CPI	-0.14	-0.33	-0.14	0.14	0.10	-0.05	0.32	-0.13
	num_sc	0.09	-0.22	-0.27	-0.28	-0.29	-0.30	0.05	0.08

Table 4.4: Comparison of neural network predictive performance with conventional models for different lake groups and datasets. Values are the normalized mean square errors of predicted values for the optimal models. Values in bold italics are prediction errors greater than one, indicating poor model performance. Node, decay, and seed values that minimized error on the validation datasets are shown. Models included supervised neural networks (NNET), Multiple Linear Regression (MLR), MLR with stepwise variable selection, Generalized Additive Models (GAM), regression trees, and regression trees with an optimal complexity parameter. All models used IBI scores as a single response variable. See tables D.1 and D.2 and figs. D.4 and D.5 for specific model information.

		Dataset error		
Group	Model	Training	Validation	Test
All	NNET	0.151	0.386	0.442
	MLR	0.263	0.448	0.452
	MLR step	0.263	0.443	0.447
	GAM	0.168	***1.381***	0.596
	Tree	0.201	0.831	0.558
	Tree (cp)	0.358	0.610	0.452
Northern	NNET	0.163	***1.050***	***1.515***
	MLR	0.725	***1.088***	0.809
	MLR step	0.754	***1.042***	0.794
	GAM	-	-	-
	Tree	0.524	***1.315***	***1.301***
	Tree (cp)	0.858	***1.067***	***1.092***
Southern	NNET	0.190	0.533	***1.138***
	MLR	0.365	0.647	0.747
	MLR step	0.378	0.647	0.769
	GAM	0.252	0.627	0.823
	Tree	0.321	0.945	***1.714***
	Tree (cp)	0.647	0.965	***1.327***

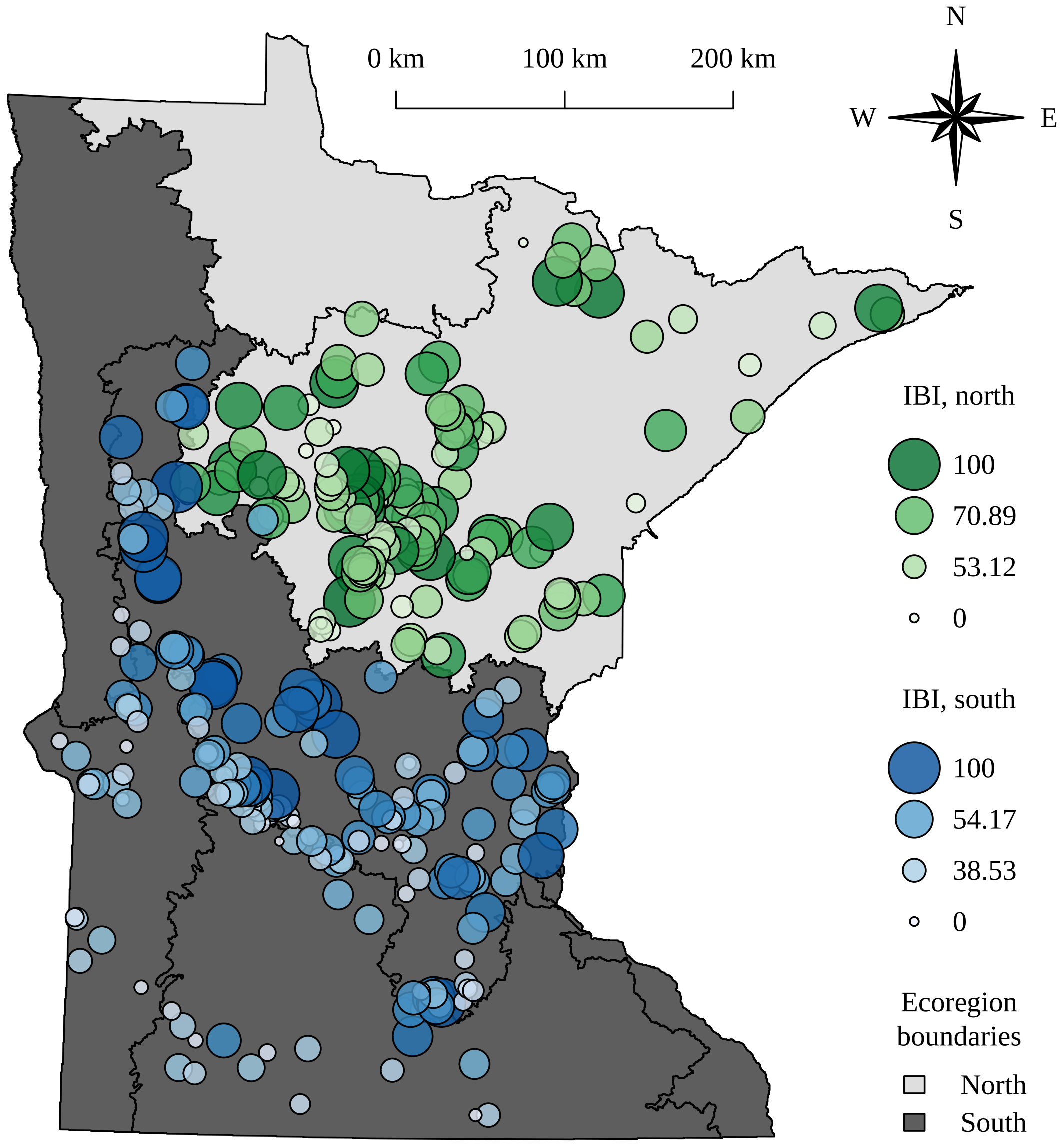


Figure 4.1: Locations of 332 lakes with IBI scores used to develop neural networks. Lakes are separated into northern ($n = 145$) and southern ($n = 187$) groups based on ecoregion boundaries (level III, Omernik, 1987). Point size and color are scaled continuously in proportion to IBI score.

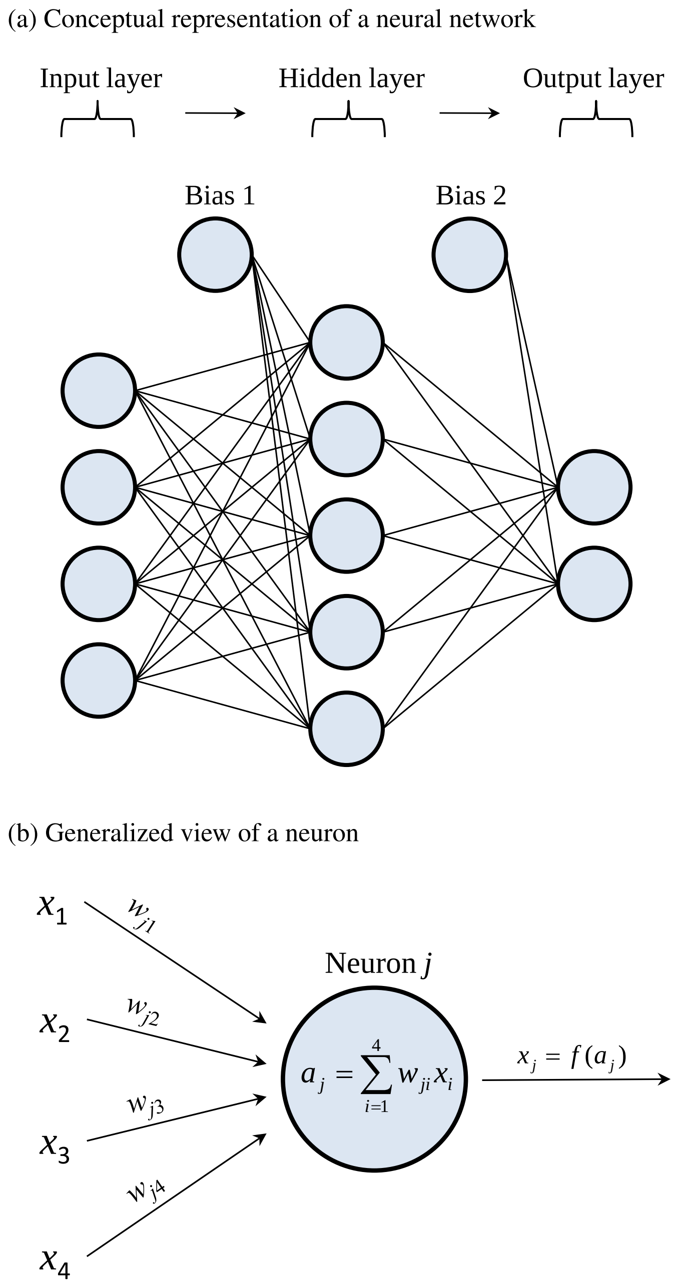
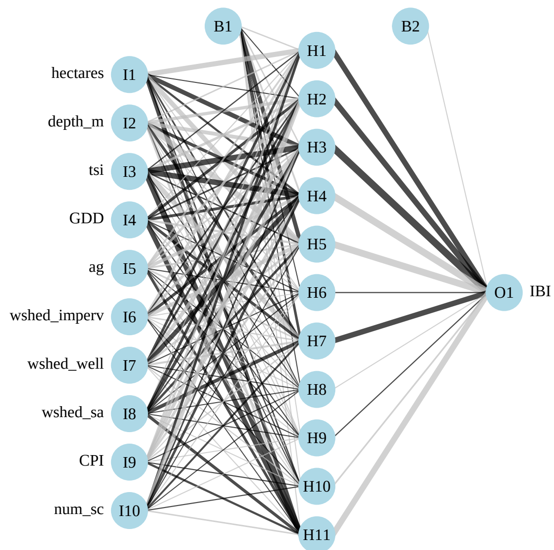
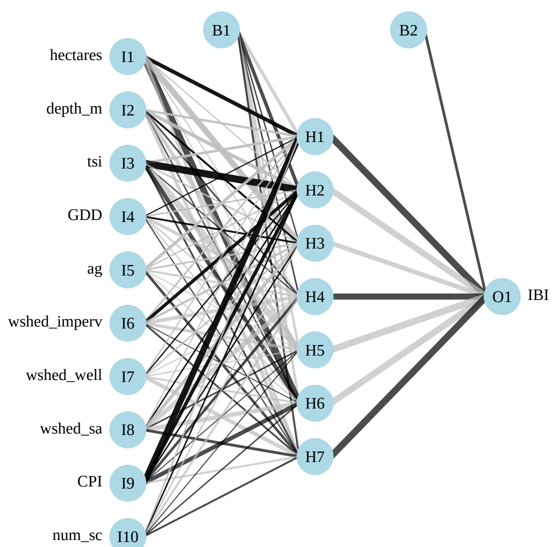


Figure 4.2: Conceptual representation of a three-layer, feed-forward, supervised neural network (a) and a component neuron or node (b). The input, hidden, and output layers are linked by weighted connections (lines) between nodes (circles). Bias layers are constant values similar to intercepts in regression models. Progression through the network is unidirectional. The activation value a_j of neuron j is determined from the summation of input variables $x_1, \ldots, x_4$ multiplied by the connection weights $w_{j1}, \ldots, w_{j4}$. The transfer function $f(a_j)$ converts the activation value to the output value x_j.

(a) IBI model for all lakes



(b) IBI model for northern lakes



(c) IBI model for southern lakes

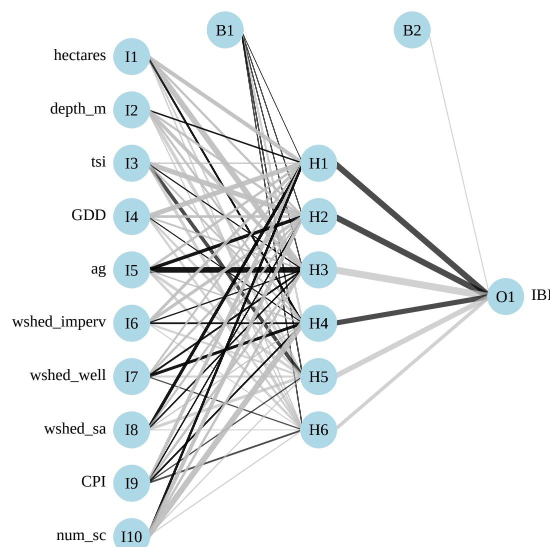


Figure 4.3: Optimal neural networks for IBI scores that minimized prediction error on the validation datasets for each lake group (table 4.1). Connections between layers are colored by sign (positive black, negative grey) and have width in proportion to relative weights (Özesmi and Özesmi, 1999).

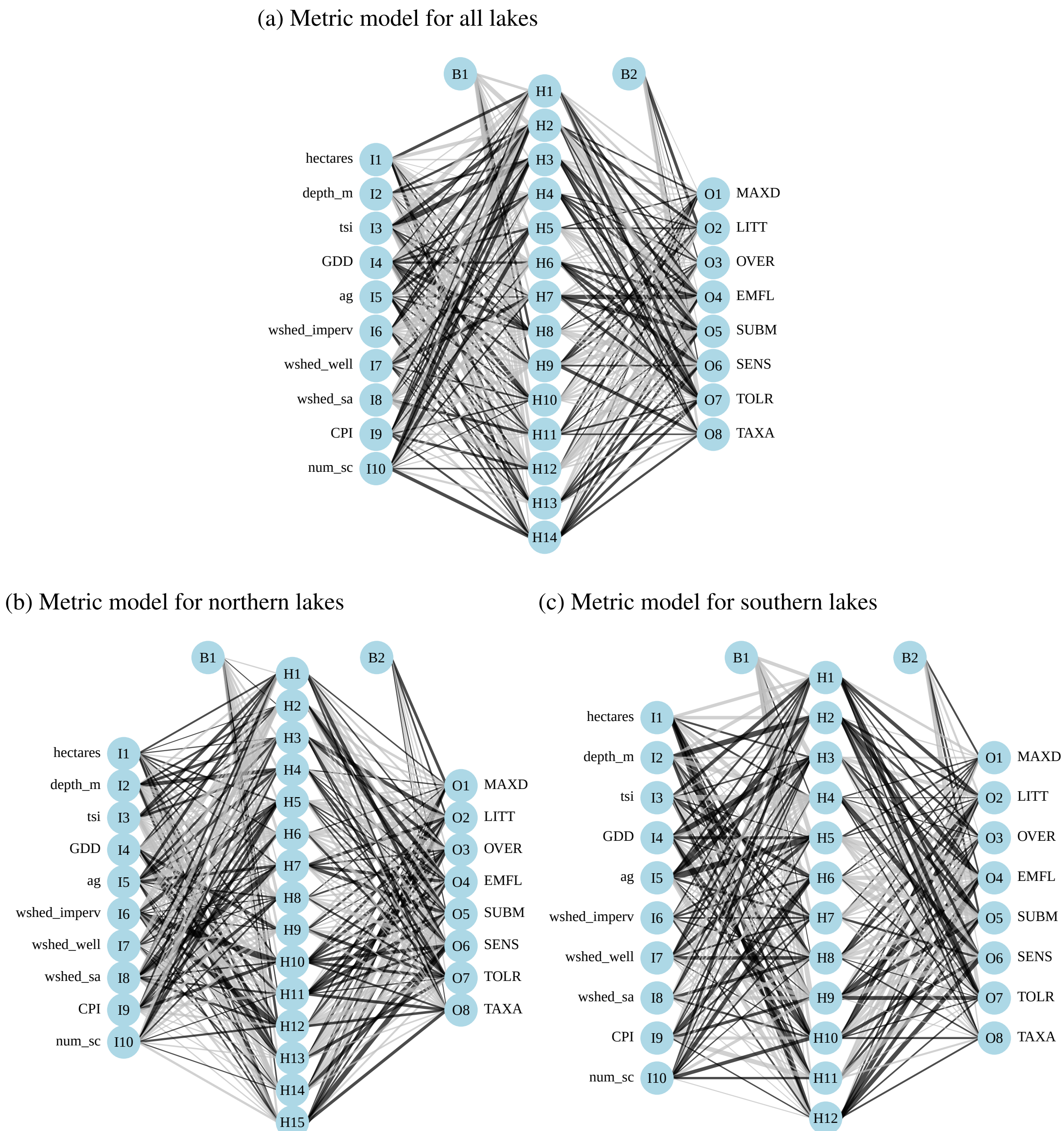


Figure 4.4: Optimal neural networks for metrics that minimized prediction error on the validation datasets for each lake group (table 4.1). Subfigures (a) to (c) illustrate the optimal models for TAXA, MAXD, and TAXA, respectively. Connections between layers are colored by sign (positive black, negative grey) and have width in proportion to relative weights (Özesmi and Özesmi, 1999).

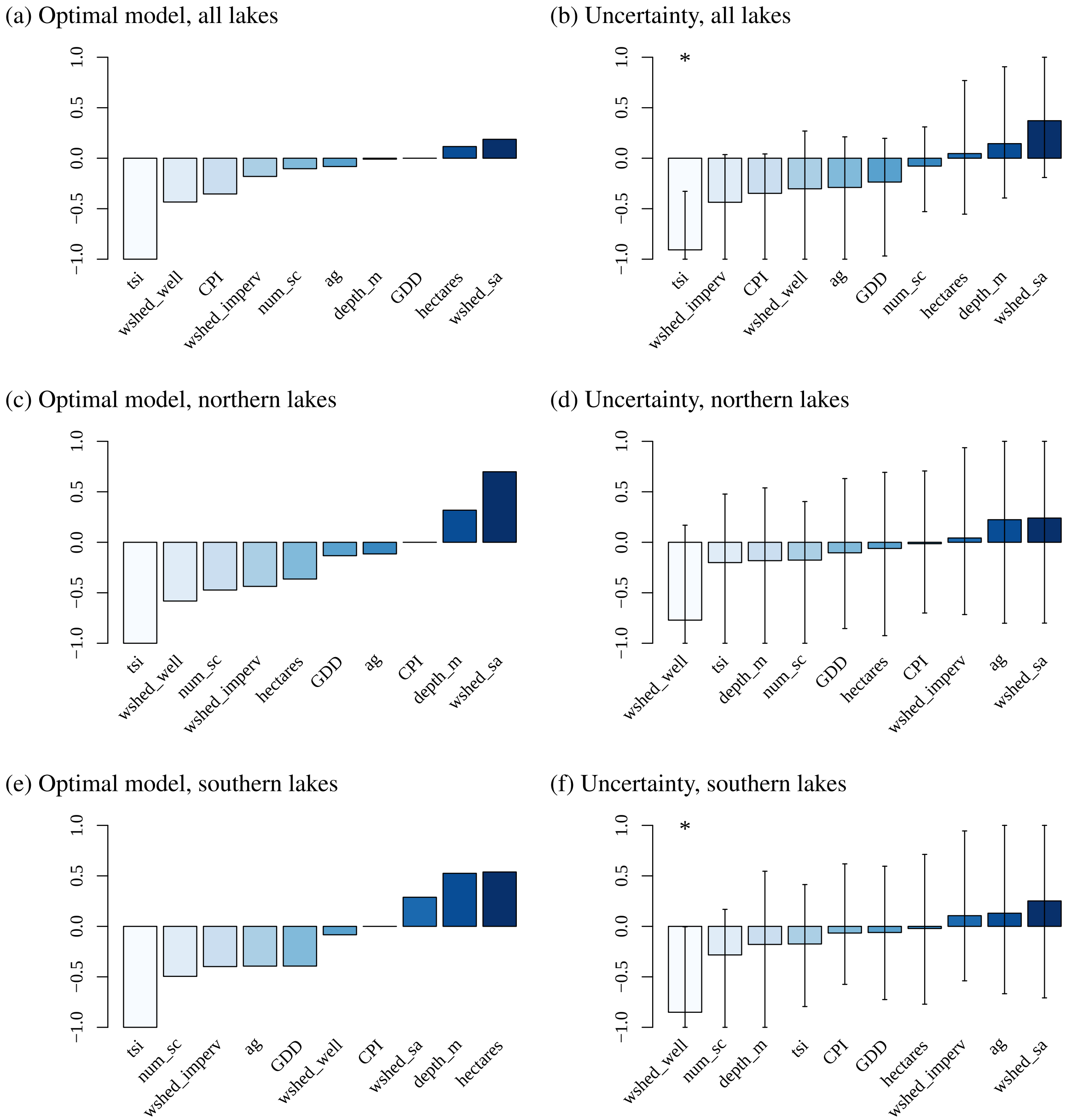
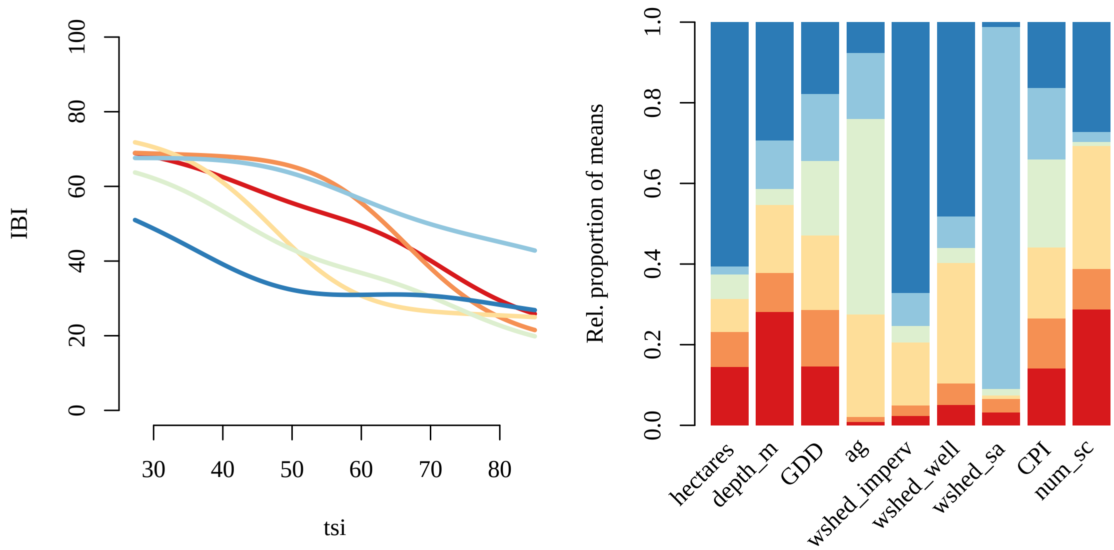


Figure 4.5: Relative importance (Garson, 1991; Goh, 1995) values of explanatory variables used in neural networks for IBI scores. Subfigures (a), (c), and (e) illustrate relative importance values for the optimal models and (b), (d), and (f) illustrate uncertainty associated with relative importance using mean, 2.5th, and 97.5th percentile values from bootstrap analyses (* interval does not include zero). Subfigures (a) and (b) show all lakes, (c) and (d) show northern lakes, and (e) and (f) show southern lakes. See table 4.3 for results of bootstrap analyses with metrics.

(a) All lakes



(b) Southern lakes

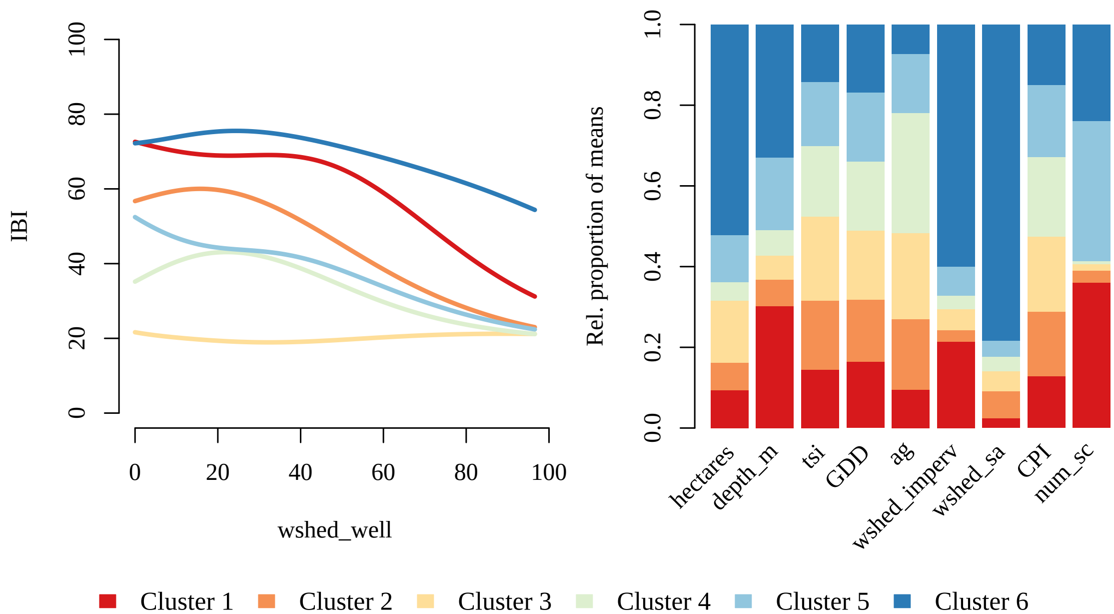


Figure 4.6: Response of IBI scores to explanatory variables indicated by neural networks (see table 4.2). Subfigure (a) shows IBI response to lake trophic state (*tsi*) for all lakes and (b) shows IBI response to watershed well density (*wshed_well*) for southern lakes. IBI response is specific to lake clusters identified using an agglomerative clustering technique. All other explanatory variables were held constant at the mean values for each lake cluster. The bar plots indicate approximate mean value for each explanatory variable relative to all lake clusters.

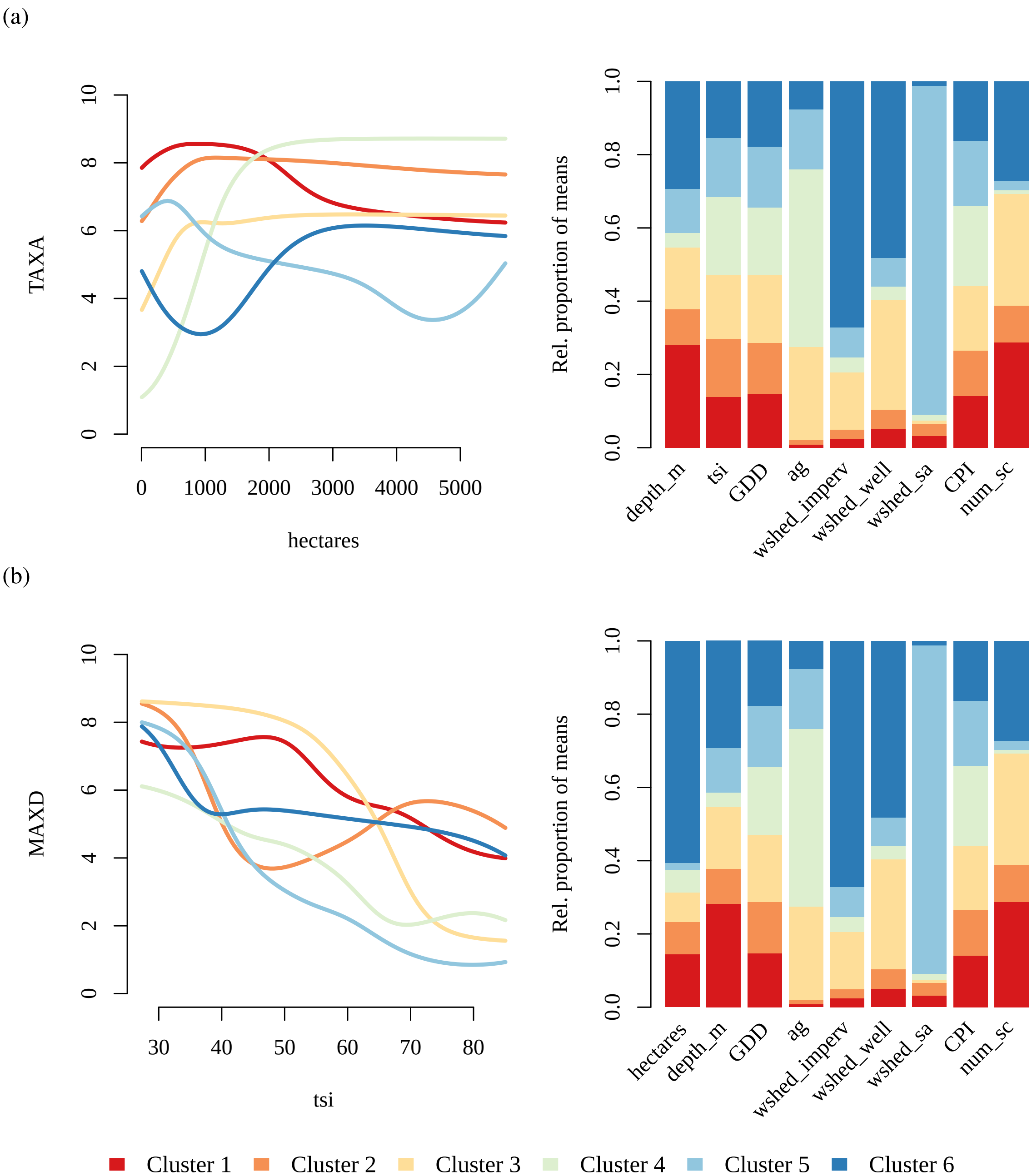


Figure 4.7: Response of TAXA and MAXD metrics to explanatory variables indicated by neural networks for all lakes (see table 4.3). Subfigure (a) shows TAXA response to lake size (*hectares*) and (b) shows MAXD response to lake trophic state (*tsi*). Metric response is specific to lake clusters identified using an agglomerative clustering technique. All other explanatory variables were held constant at the mean values for each lake cluster. The bar plots indicate approximate mean value for each explanatory variable relative to all lake clusters.

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Appendix A

Chapter 1 Additional information

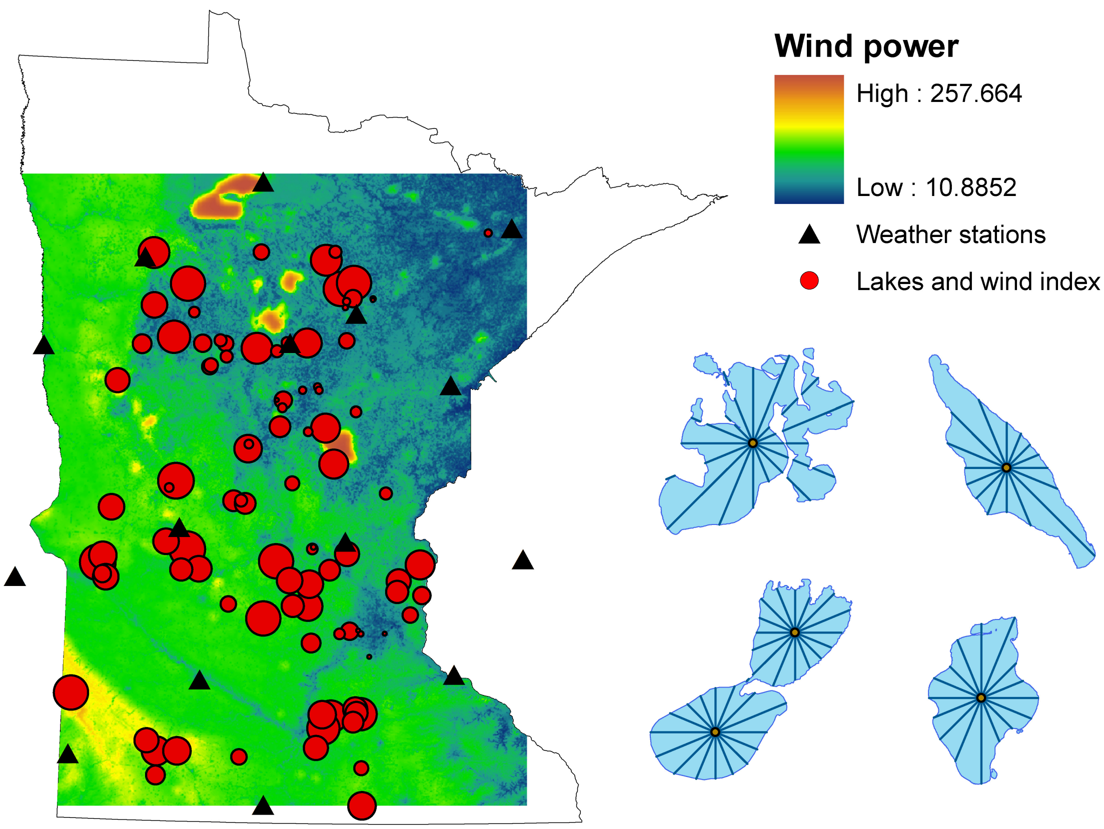


Figure A.1: Example of data used to calculate a wind index for each lake. The wind index is a whole-lake measure that combines wind strength and fetch (*sensu* Cross and McInerny, 2006). The index is calculated using a summed product of data from the nearest weather station (triangles), a measure of wind power (color ramp), and fetch measurements from radial lines at each lake (lower right). Lake points are in proportion to relative wind index values.

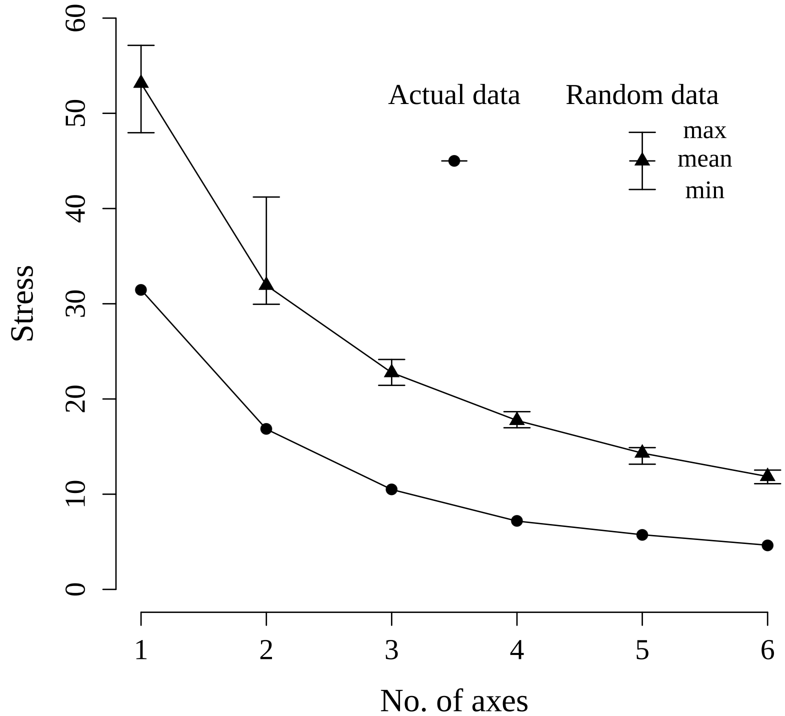


Figure A.2: Screeplot for nonmetric multidimensional scaling to evaluate comparable groups of lakes. The screeplot shows final stress values of the ordination as a function of number of axes. Ordinations were based on dissimilarity measures between lakes determined from twenty-five lake characteristics (table 1.1). Actual ordination results are shown on the bottom line whereas data were randomized on the top line to determine whether results were not obtained by random chance.

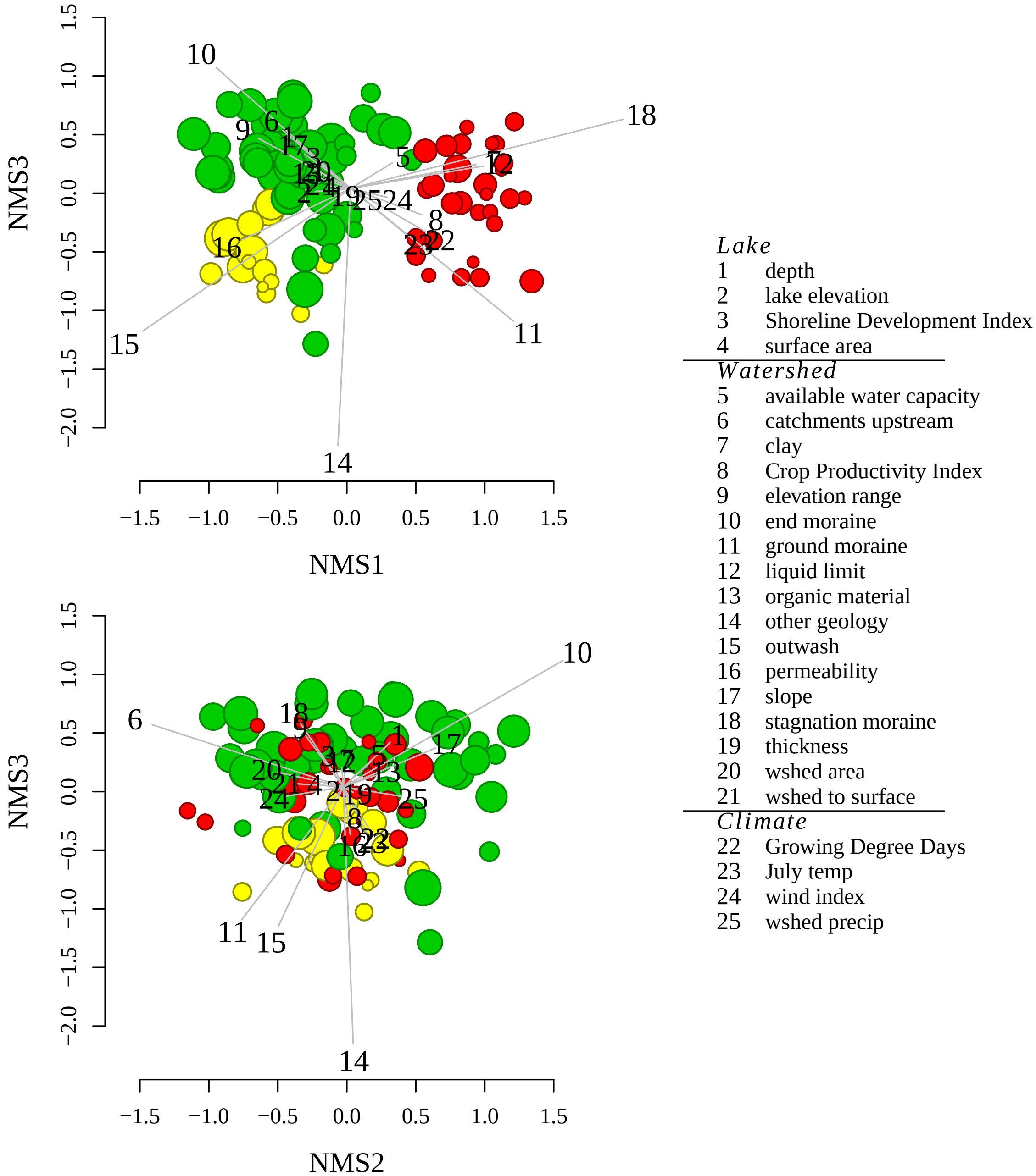


Figure A.3: Ordination results obtained from nonmetric multidimensional scaling for axes 1 (NMS1), 2 (NMS2), and 3 (NMS3). Orientation and length of vectors originating from the origin indicate the sign and magnitude of the correlation for each environmental variable with each axis. Data points are color-coded by group as in fig. 1.3 (top-right, k = 3) and size is proportional to IBI score. See table 1.1 for description of variables (grouped by lake, watershed, and climate characteristics). See fig. 1.4 for a comparison of axes 1 and 2.

Appendix B

Chapter 2 Additional information

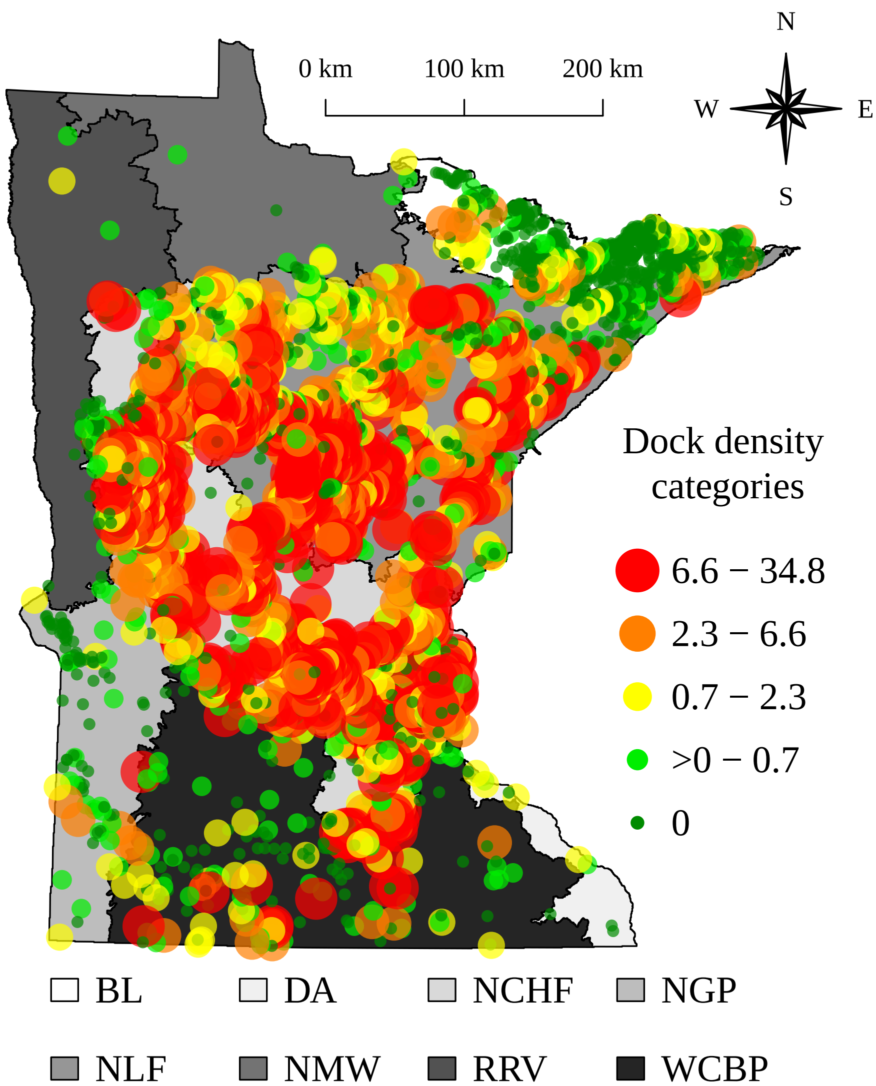


Figure B.1: Locations and dock densities (docks per shoreline km) of 4,261 lakes analysed using the dock analysis workflow. Lake points are shaded using density categories in fig. 2.5b. Point size is also in proportion to dock density. BL = Border Lakes, DLA = Driftless Area, NCHF = North Central Hardwood Forests, NGP = Northern Glaciated Plains, NLF = Northern Lakes and Forests, NMW = Northern Minnesota Wetlands, RRV = Red River Valley, and WCBP = Western Cornbelt Plains.

Listing B.1: Python script used to process aerial images for the shoreline correction process of the dock analysis workflow. See fig. 2.1 for a conceptual representation.

```python
"""
Shoreline extraction v5
Prepared May 2011, M. Beck

classification requires lake image, 10k lakes layer, all in workspace
signature files are not deleted in workspace
"""

import arcgisscripting,time,datetime,os,glob,shutil
start = time.time(); class_error, fill_error = list(), list()
gp = arcgisscripting.create()
gp.overwriteoutput = 1
gp.CheckOutExtension("Spatial")

gp.Workspace = "C:\\Projects\\GIS data\\OBIA nearshore\\biological_response_lakes\\clipped_images\\"

dat_ls = open(gp.Workspace + "\\dow_miss.txt").read().split()

DOWNUM = dat_ls

def sel_class(arg):
    classes = range(0,int(list(open(arg))[len(list(open(arg)))-9].split()[0]))
    class_rows = [21+12*i for i in classes]  #these index values cause errors if incorrect
    meanstr = [list(open(arg))[i].split() for i in class_rows]
    meannum = [[float(w) for w in meanstr[i]] for i in classes]
    all_val, means_rgb, r_div_ir, blue_div_ir, max_band = {}, {}, {}, {}, {}
    for i in classes:
        all_val.update({i+1:[((meannum[i][0]+meannum[i][1]+meannum[i][2])+meannum[i][3])/4,
            (meannum[i][0]+meannum[i][1]+meannum[i][2])/3,(meannum[i][0]/meannum[i][3])]})
        means_rgb.update({i+1:(meannum[i][0]+meannum[i][1]+meannum[i][2])/3})
        r_div_ir.update({i+1:(meannum[i][0]/meannum[i][3])})
        blue_div_ir.update({i+1:(meannum[i][2]/meannum[i][3])})
        max_band.update({i+1:1+meannum[i].index(max(meannum[i]))})
    min_rgb = min(means_rgb.values())
    for i in r_div_ir.keys():
        if r_div_ir[i] < 1:
            del(r_div_ir[i])
        if means_rgb[i] > 150:
            del(means_rgb[i])
        if blue_div_ir[i] < 1:
            del(blue_div_ir[i])
    if len(list(set(r_div_ir.keys()) & set(means_rgb.keys()) & set(blue_div_ir.keys()))) > 5:
        dat = list(set(r_div_ir.keys()) & set(means_rgb.keys()) & set(blue_div_ir.keys()))
        for i in max_band.keys():
            if max_band[i] == 3:
                if i not in set(dat):
                    dat.append(i)
        dat.sort(); return dat
    else:
        dat, dat2, dat3 = list(), list(), list()
        for i in all_val.keys():
            if all_val[i][0] < min(all_val.values())[0]+15 and all_val[i][2] > 0.7:
                dat.append(i)
            if all_val[i][1] < min_rgb+15 and all_val[i][2] > 0.8:
                dat2.append(i)
            if all_val[i][0]/max([all_val[w][0] for w in all_val.keys()]) < 0.6:
                dat3.append(i)
        if len(dat) <= 5:
            if len(dat2) <=5:
                return dat3
            else: return dat2
        else: return dat

def check_clust(arg):
    iso_test = arg
    classes = range(0,int(list(open(iso_test))[len(list(open(iso_test)))-9].split()[0]))
    cov_rows = [23+12*i+w for i in classes for w in range(0,4)] #these index values cause errors if incorrect
    covstr = [list(open(iso_test))[i].split() for i in cov_rows]
    covstr = [covstr[i][int(covstr[i][0])] for i in range(0,len(covstr))]
    covnum = [float(w) for w in covstr]
    if 0 in set(covnum):
        return 'fail'
    else:
        return 'pass'

def remap(arg):
    dat = ''
    for i in range(0,len(arg)):
        if [i] != range(0,len(arg))[-1:]:
            dat = str(dat + str(arg[i]) + " 1" + ";")
        else:
            dat = str(dat + str(arg[i]) + " 1")
    return dat

```

```
def rasts(arg):
    rast = gp.ListRasters("g" + str(arg) + "*","GRID").next()
    if rast == None: print "error"
    elif rast[0:5] == "g" + str(arg) + "tmp" and 'c' not in rast: return rast

def delete_temps(arg1,arg2):
    gp.Delete_management("g1tmp.img")
    temps, temps2 = range(1,arg1), [rasts(y) for y in range(1,arg2)]
    [gp.Delete_management(DOW + "_temp" + str(y) + ".shp") for y in temps]
    try:
        [gp.Delete_management(y) for y in temps2]
    except:
        for y in temps2:
            for x in glob.glob(gp.Workspace + "\\g" + str(y) + "*"):
                try: os.remove(x)
                except: shutil.rmtree(x)
        tables = gp.ListTables("g*","INFO")
        table = tables.next()
        while table:
            gp.Delete_management(table)
            table = tables.next()

for z in range(0,len(DOWNUM)):
    try:

        DOW = DOWNUM[z]
        extent = DOWNUM[z] + "_lake.img"

        print "\n" + DOW + "; lake " + str(z + 1) + " of " + str(len(DOWNUM))

        gp.makefeaturelayer('biol_resp_lakes.shp','lyr1')
        gp.selectlayerbyattribute('lyr1', 'NEW_SELECTION', "\"DOWLKNUM\" = " + "'" + str(DOW) + "'")
        rows = gp.searchcursor('lyr1'); row = rows.next()
        if row == None:
            gp.selectlayerbyattribute('lyr1', 'NEW_SELECTION', "\"MAIN_DOW\" = " + "'" + str(DOW) + "'")
        gp.copyfeatures('lyr1', DOW + '_temp1.shp')

        del row, rows

        print "converting raster format"
        gp.CopyRaster_management(extent, "g1tmp.img")
        gp.RasterToOtherFormat_conversion("g1tmp.img", gp.Workspace, "GRID")

        print "extracting buffer area"
        gp.buffer_analysis(DOW + "_temp1.shp", DOW + "_temp2.shp", "50")
        gp.clip_management(rasts(1), '#', 'g2tmp', DOW + "_temp2.shp", '#', 'ClippingGeometry') #extract by mask did not
            work

        print "classifying"
        try:
            iso_run = range(30,41) + range(29,18,-1)
            for i in iso_run:
                if i != 19:
                    gp.IsoCluster_sa(rasts(2), DOW + "_sc.gsg", i, 100, 2, 4)
                    if check_clust(gp.Workspace + "\\" + DOW + "_sc.gsg") == 'fail':
                        print "      clustering fail with " + str(i) + "..."
                        continue
                    else:
                        print "      clustering pass with " + str(i) + "..."
                        gp.MLClassify_sa(rasts(2), DOW + "_sc.gsg", "g3tmp", "#", "SAMPLE")
                        classes = range(0,int(list(open(gp.Workspace + "/" + DOW + "_sc.gsg"))[len(list(open(gp.
                            Workspace +
                            "/" + DOW + "_sc.gsg")))-9].split()[0]))
                        classes_rast = gp.GetRasterProperties(rasts(3), "UNIQUEVALUECOUNT")
                        if classes_rast == len(classes):
                            print "      classification successful"
                            del classes, classes_rast, iso_run
                            proceed = "YES"
                            break
                        else:
                            print "      classification rerun"
                            continue
                else:
                    print "      clustering unsuccessful"
                    class_error.append(DOW)
                    proceed = "NO"
        except:
            class_error.append(DOW)
            proceed = "NO"

        if proceed == "NO":
            gp.copyfeatures(DOW + "_temp1.shp", DOW + "_lake.shp")
            delete_temps(3,3)
            continue; del proceed
        else:
            print "selecting water"
            gp.Reclassify_sa(rasts(3), "VALUE", remap(sel_class(gp.Workspace + "\\" + DOW + "_sc.gsg")),
                "g4tmp", "NODATA")
```

```
            gp.RasterToPolygon_conversion(rasts(4), DOW + "_temp3.shp", "NO_SIMPLIFY")
            gp.Dissolve_management(DOW + "_temp3.shp", DOW + "_temp4.shp", "FID", "#", "SINGLE_PART")
            gp.makefeaturelayer(DOW + "_temp4.shp","lyr2")
            gp.SelectLayerByLocation("lyr2", "INTERSECT", "lyr1", "#", "#", "NEW_SELECTION")
            gp.CopyFeatures("lyr2", DOW + "_temp5.shp")

            print "filling holes"
            cont_size = "5"
            try:
                gp.buffer_analysis(DOW + "_temp5.shp", DOW + "_temp6.shp", cont_size, "#", "#","LIST", "FID")
                gp.buffer_analysis(DOW + "_temp6.shp", DOW + "_lake.shp", "-" + cont_size)
                delete_temps(7,5)
            except:
                print "      failed"
                gp.copyfeatures(DOW + "_temp1.shp", DOW + "_lake.shp")
                fill_error.append(DOW)
                delete_temps(6,5)

        print "elapsed time " + str(datetime.timedelta(seconds = round(time.time() - start)))

    except:

        print gp.GetMessages()

print "\nelapsed time " + str(datetime.timedelta(seconds = round(time.time() - start))) + "; " + "average time per " + \
    "lake " + str(datetime.timedelta(seconds = round((time.time() - start)/len(DOWNUM)))) + "\n" + \
    str(len(class_error)) + " lakes with classification errors; " + str(len(fill_error)) + \
    " lakes with filling errors"
```

Listing B.2: Python script used to process aerial images for the dock extraction process of the dock analysis workflow. See fig. 2.1 for a conceptual representation.

```python
"""
Nearshore classification of docks
v5 Prepared April 2011, M. Beck
modified slightly May 2012 for ArcMap10

classification requires segmented lake image, corrected lake polygon, lake image, 10k lakes layer, text file with DOWs
"""

import arcgisscripting,time,datetime,os,glob,shutil
gp = arcgisscripting.create()
gp.OverwriteOutput = 1
gp.CheckOutExtension("Spatial")

start = time.time(); empties = list(); class_fails = list(); write_poly = "yes"
gp.Workspace = "C:\\Projects\\GIS data\\OBIA nearshore\\biological_response_lakes\\clipped_images\\"
seg_path = "C:\\Projects\\GIS data\\OBIA nearshore\\biological_response_lakes\\segmented_images\\"
tenk = os.path.join(gp.workspace,'biol_resp_lakes.shp')

dat_ls = open(gp.Workspace + "\\dow_miss.txt").read().split()

DOWNUM = dat_ls

def sel_class(arg):
    classes = range(0,int(list(open(arg))[len(list(open(arg)))-9].split()[0]))
    class_rows = [21+12*i for i in classes]
    meanstr = [list(open(arg))[i].split() for i in class_rows]
    meannum = [[float(w) for w in meanstr[i]] for i in classes]
    means_rgb = {}
    for i in classes:
        means_rgb.update({i+1:(meannum[i][0]+meannum[i][1]+meannum[i][2])/3})
    dat = list()
    if max(means_rgb.items())[1] <= 150:
        dat = sorted(means_rgb, key=means_rgb.__getitem__)[-3:]
    else:
        for i in range(0,len(means_rgb)):
            if means_rgb.items()[i][1] > 150:
                dat.append(means_rgb.items()[i][0])
    return sorted(dat)

def remap(arg):
    dat = ''
    for i in range(0,len(arg)):
        if [i] != range(0,len(arg))[-1:]:
            dat = str(dat + str(arg[i]) + " 1" + ";")
        else:
            dat = str(dat + str(arg[i]) + " 1")
    return dat

def check_clust(arg):
    iso_test = arg
    classes = range(0,int(list(open(iso_test))[len(list(open(iso_test)))-9].split()[0]))
    cov_rows = [23+12*i+w for i in classes for w in range(0,4)]
    covstr = [list(open(iso_test))[i].split() for i in cov_rows]
    covstr = [covstr[i][int(covstr[i][0])] for i in range(0,len(covstr))]
    covnum = [float(w) for w in covstr]
    if 0 in set(covnum):
        return 'fail'
    else:
        return 'pass'

def num_poly(arg):
    if write_poly != "no":
        write_file = open(os.path.join(gp.workspace,'dock_info.txt'),'a')
        def get_rows(arg):
            rows = gp.searchcursor(arg)
            row = rows.next()
            rownum = list()
            while row:
                rownum.append(row.FID)
                row = rows.next()
            return len(rownum); del rows
        dat = [DOW]
        [dat.append(str(v)) for v in [get_rows(DOW + i + ".shp") for i in ["_final" + str(w) for w in range(1,arg)]]]
        if arg == 0:
            [dat.append(u) for u in list(['NA'] * 5)]
        if arg == 3:
            [dat.append(u) for u in ('0','0')]
        if arg == 4:
            dat.append('0')
        if arg != 0:
            dat.append(get_rows(DOW + "_docks_unc.shp"))
        dat.append(str(datetime.timedelta(seconds = round(time.time() - start_z))))
        dat.append(time.asctime())
        strs = ''
```

```
        for i in range(0,len(dat)):
            if [i] != range(0,len(dat))[-1:]:
                strs = str(strs + str(dat[i]) + ",")
            else:
                strs = str(strs + str(dat[i]))
        write_file.write(strs + "\n")
        write_file.close()

def rasts(arg):
    rast = gp.ListRasters("g" + str(arg) + "*","GRID").next()
    if rast == None: print "error"
    elif rast[0:5] == "g" + str(arg) + "tmp" and 'c' not in rast: return rast
    del rast

def delete_temps(arg1,arg2,arg3):
    gp.Delete_management("g1tmp.img")
    temps, temps2 = range(1,arg1), [rasts(y) for y in range(1,arg2)]
    [gp.Delete_management(DOW + "_temp" + str(y) + ".shp") for y in temps]
    if arg1 > 4:
        [gp.Delete_management(y) for y in (DOW + "_segtemp1.img", DOW + "_segtemp2.shp")]
    if arg3 != 0:
        temps3 = range(1,arg3)
        [gp.Delete_management(DOW + "_final" + str(y) + ".shp") for y in temps3]
    try:
        [gp.Delete_management(y) for y in temps2]
    except:
        for y in temps2:
            for x in glob.glob(gp.Workspace + "\\g" + str(y) + "*"):
                try: os.remove(x)
                except: shutil.rmtree(x)
        tables = gp.ListTables("g*","INFO")
        table = tables.next()
        while table:
            gp.Delete_management(table)
            table = tables.next()

if write_poly == "yes": print "\nwriting output to dock_info.txt"

for z in range(0,len(DOWNUM)):
    try:
        start_z = time.time()
        DOW = DOWNUM[z]
        extent = DOWNUM[z] + "_lake.img"
        lake_poly = DOW + "_lake.shp"
        print "\n" + DOW + "; lake " + str(z + 1) + " of " + str(len(DOWNUM))

        print "converting raster format"
        gp.CopyRaster_management(extent, "g1tmp.img")
        gp.RasterToOtherFormat_conversion("g1tmp.img", gp.Workspace, "GRID")

        print "extracting near shore"
        gp.buffer_analysis(lake_poly, DOW + "_temp1.shp", "-70")
        gp.makefeaturelayer(DOW + "_temp1.shp", "lyr1")
        gp.makefeaturelayer(lake_poly, "lyr2")
        gp.union_analysis("lyr1; lyr2", DOW + "_temp2.shp")
        gp.makefeaturelayer(DOW + "_temp2.shp","lyr3","\"BUFF_DIST\" = 0")
        gp.copyfeatures("lyr3", DOW + "_temp3.shp")
        gp.clip_management(rasts(1), '#', 'g2tmp', DOW + "_temp2.shp", '#', 'ClippingGeometry')

        print "classifying"
        iso_run = range(30,41) + range(29,18,-1)
        for i in iso_run:
            if i != 19:
                try:
                    gp.IsoCluster_sa(rasts(2), DOW + "_de.gsg", i, 100, 2, 4)
                except:
                    print "      clustering fail with " + str(i) + "..."; continue
                if check_clust(gp.Workspace + "/" + DOW + "_de.gsg") == 'fail':
                    print "      clustering fail with " + str(i) + "..."
                    continue
                else:
                    print "      clustering pass with " + str(i) + "..."
                    try:
                        gp.MLClassify_sa(rasts(2), DOW + "_de.gsg", "g3tmp", "#", "SAMPLE")
                    except:
                        print gp.getmessages() + "\n      classification unsuccessful"
                        delete_temps(4,3,0)
                        proceed = "NO"; break
                    classes = range(0,int(list(open(gp.Workspace + "/" + DOW + "_de.gsg"))[len(list(open(gp.Workspace +
                        "/" + DOW + "_de.gsg")))-9].split()[0]))
                    classes_rast = gp.GetRasterProperties(rasts(3), "UNIQUEVALUECOUNT")
                    if classes_rast == len(classes):
                        print "      classification successful"
                        del classes, classes_rast, iso_run
                        proceed = "YES"
                        break
                    else:
                        print "      classification rerun"
```

```
                continue
    else:
        print "     clustering unsuccessful"
        num_poly(0); delete_temps(4,3,0)
        proceed = "NO"

if proceed == "NO":
    del proceed, iso_run; class_fails.append(DOW)
    continue
else:
    gp.Reclassify_sa(rasts(3), "VALUE", remap(sel_class(gp.Workspace + "/" + DOW + "_de.gsg")),
        "g4tmp", "NODATA")
    gp.RasterToPolygon_conversion(rasts(4), DOW + "_final1.shp", "NO_SIMPLIFY")

    print "combining with segmentation"
    gp.clip_management(seg_path + '\\' + DOW + "_seg.img", '#', DOW + "_segtemp1.img", DOW + "_temp3.shp",
        '#', 'ClippingGeometry')
    gp.RasterToPolygon_conversion(DOW + "_segtemp1.img", DOW + "_temp4.shp", "NO_SIMPLIFY")
    gp.AddField_management(DOW + "_temp4.shp", "area_m2", "DOUBLE", "25", "2")
    gp.CalculateField_management(DOW + "_temp4.shp", "area_m2", "float(!shape.area!)","PYTHON")
    gp.makefeaturelayer(DOW + "_temp4.shp", "lyr4", "\"area_m2\" < 200")
    gp.copyfeatures("lyr4", DOW + "_segtemp2.shp")
    gp.Clip_analysis(DOW + "_final1.shp", DOW + "_segtemp2.shp", DOW + "_final2.shp")
    rows = gp.SearchCursor(DOW + "_final2.shp")
    row = rows.next()
    if row == None:
        print "     empty layer"
        gp.copyfeatures(DOW + "_final2.shp", DOW + "_docks_unc.shp")
        del row, rows; empties.append(DOW)
        num_poly(3); delete_temps(5,5,3)

    else:
        print "filtering by size"
        gp.MultipartToSinglepart_management (DOW + "_final2.shp", DOW + "_temp5.shp")
        gp.AddField_management(DOW + "_temp5.shp", "area_m2", "DOUBLE", "25", "2")
        gp.CalculateField_management(DOW + "_temp5.shp", "area_m2", "float(!shape.area!)",
            "PYTHON")
        gp.makefeaturelayer(DOW + "_temp5.shp", "lyr5", "\"area_m2\" > 4 AND \"area_m2\" < 650")
        gp.copyfeatures("lyr5", DOW + "_final3.shp")
        rows = gp.SearchCursor(DOW + "_final3.shp")
        row = rows.next()
        if row == None:
            print "     empty layer"
            gp.copyfeatures(DOW + "_final3.shp", DOW + "_docks_unc.shp")
            del row, rows; empties.append(DOW)
            num_poly(4); delete_temps(6,5,4)

        else:
            print "filtering by object reflectance"
            max_r, max_g, max_b, mean_r, mean_g, mean_b = list(), list(), list(), list(), list(), list()
            def row_append(arg1, arg2, arg3):
                rows = gp.SearchCursor(str("out" + arg3))
                row = rows.next()
                while row:
                    arg1.append(row.MAX)
                    arg2.append(row.MEAN)
                    row = rows.next()
            for i in ["c1","c2","c3"]:
                gp.ZonalStatisticsAsTable_sa(DOW + "_final3.shp", "FID", rasts(2) + i, str("out" + i),
                    "DATA")
                if i == "c1":
                    row_append(max_r, mean_r, i)
                elif i == "c2":
                    row_append(max_g, mean_g, i)
                elif i == "c3":
                    row_append(max_b, mean_b, i)
                gp.Delete_management(str("out" + i))
            fid_list = list()
            for i in range(0,len(mean_g)):
                fid_list.append([i,max_r[i],max_g[i],max_b[i],mean_g[i]-((mean_b[i] + mean_r[i])/2)])
            del max_r, max_g, max_b, mean_r, mean_g, mean_b
            fid_sel = list(); fid_sel2 = list()
            for i in fid_list:
                for y in range(1,4):
                    if i[y] > 210:
                        fid_sel.append(i[0])
                        break
                    else:
                        continue
            for i in fid_sel:
                if(fid_list[i][4] < 15):
                    fid_sel2.append(str(fid_list[i][0]))
            del fid_list, fid_sel
            if len(fid_sel2) == 0:
                print "     empty layer"
                gp.createfeatureclass_management(gp.workspace, DOW + "_docks_unc.shp", "POLYGON",
                    DOW + "_final3.shp", "SAME_AS_TEMPLATE", "SAME_AS_TEMPLATE", DOW + "_final3.shp")
                del row, rows, fid_sel2; empties.append(DOW)
```

```
                        num_poly(4); delete_temps(6,5,4)

                    else:
                        gp.makefeaturelayer(DOW + "_final3.shp","lyr6")
                        for i in range(0,len(fid_sel2)):
                            gp.selectlayerbyattribute("lyr6", "ADD_TO_SELECTION", "\"FID\" = " + fid_sel2[i])
                        gp.copyfeatures("lyr6", DOW + "_final4.shp"); del fid_sel2

                        print "clean up"
                        gp.makefeaturelayer(DOW + "_final4.shp","lyr7")

                        gp.makefeaturelayer(tenk,'lyr8')
                        gp.selectlayerbyattribute('lyr8', 'NEW_SELECTION', "\"DOWLKNUM\" = " + "'" + str(DOW) + "'")
                        rows = gp.searchcursor('lyr8'); row = rows.next()
                        if row == None:
                            gp.selectlayerbyattribute('lyr8', 'NEW_SELECTION', "\"MAIN_DOW\" = " + "'" + str(DOW) + "'")

                        gp.SelectLayerByLocation("lyr7", "INTERSECT", "lyr8", "#", "#", "NEW_SELECTION")
                        gp.CopyFeatures("lyr7", DOW + "_docks_unc.shp")
                        rows = gp.searchcursor(DOW + "_docks_unc.shp")
                        if  rows.next() == None:
                            print "      empty layer"
                            del proceed, row, rows; empties.append(DOW)
                            num_poly(5); delete_temps(6,5,5)
                        else:
                            del proceed, row, rows
                            num_poly(5); delete_temps(6,5,5)

        print "elapsed time " + str(datetime.timedelta(seconds = round(time.time() - start)))

    except:

        print gp.GetMessages()

print "\nelapsed time " + str(datetime.timedelta(seconds = round(time.time() - start))) + "; " + "average time per "\
    + "lake " + str(datetime.timedelta(seconds = round((time.time() - start)/len(DOWNUM)))) + "\n" + str(len(empties))\
    + " empty layers; " + str(len(class_fails)) + " unsuccessful classifications"
```

Appendix C

Chapter 3 Additional information

Table C.1: Summary of variables used in between-lake analyses for stratified groups of lakes (fig. 3.1). Response variables for each analysis included total, submersed, emergent-floating, and sensitive species richness. All other variables represent explanatory variables.

Analysis	Variable	Units	Mean (95% CI)	Range
Shallow, low dev	Total	Count	19.2 (17.9, 20.6)	2, 44
	Submersed	Count	8.3 (7.5, 9)	0, 19
	Emerge/Float	Count	7.3 (6.8, 7.8)	1, 15
	Sensitive	Count	4.4 (3.9, 4.8)	0, 11
	Dock density	No./shore km	0.9 (0.6, 1.3)	0, 12
	Surface area	Hectares	63.3 (45.8, 80.7)	2.9, 960.1
	TSI	Continuous	51.3 (50.1, 52.5)	34.1, 71.2
Deep, low dev	Total	Count	25.1 (24.4, 25.9)	2, 64
	Submersed	Count	12.4 (11.9, 12.8)	0, 27
	Emerge/Float	Count	8.3 (8.1, 8.6)	0, 22
	Sensitive	Count	3.7 (3.5, 3.9)	0, 15
	Dock density	No./shore km	4.4 (4, 4.8)	0, 23.8
	Surface area	Hectares	250.6 (209.3, 291.8)	2.3, 6458.1
	TSI	Continuous	45.5 (45, 46)	24.6, 71.2
Shallow, high dev	Total	Count	9.3 (8.4, 10.3)	0, 34
	Submersed	Count	4 (3.5, 4.6)	0, 17
	Emerge/Float	Count	3.6 (3.2, 4)	0, 12
	Sensitive	Count	0.4 (0.3, 0.5)	0, 3
	Dock density	No./shore km	1.5 (1, 1.9)	0, 17.5
	Surface area	Hectares	194.3 (134.6, 253.9)	0.9, 4390.2
	TSI	Continuous	69.2 (67.9, 70.4)	45.8, 90.1
Deep, high dev	Total	Count	18.3 (17.5, 19.2)	1, 54
	Submersed	Count	10.3 (9.9, 10.8)	0, 29
	Emerge/Float	Count	5.1 (4.9, 5.4)	0, 16
	Sensitive	Count	1.1 (1, 1.2)	0, 10
	Dock density	No./shore km	6.7 (6.1, 7.3)	0, 31.2
	Surface area	Hectares	200 (169.1, 231)	3, 3049.2
	TSI	Continuous	55.3 (54.4, 56.1)	34.3, 82.2

Table C.2: Performance of GLMs that evaluated between-lake effects of docks. Explained deviance (as proportion) is the difference between the null and residual deviance, divided by the null deviance (Zuur et al., 2009; Fox and Weisberg, 2011). Performance is shown for analyses that evaluated the entire set and stratified subsets of lakes (fig. 3.1). Response variables were total, submersed, emergent/floating, and sensitive species richness.

Analysis	Response	Explained	Null	Residual
All lakes	Total	0.46	7786	4170
	Submersed	0.21	1236	977
	Emerge/Float	0.16	962	810
	Sensitive	0.42	2659	1536
Shallow, low dev	Total	0.27	1548	1123
	Submersed	0.12	362	318
	Emerge/Float	0.05	216	206
	Sensitive	0.19	734	591
Deep, low dev	Total	0.17	1576	1313
	Submersed	0.16	293	245
	Emerge/Float	0.05	207	198
	Sensitive	0.20	658	529
Shallow, high dev	Total	0.29	1723	1219
	Submersed	0.16	314	265
	Emerge/Float	0.10	311	278
	Sensitive	0.06	333	312
Deep, high dev	Total	0.15	895	765
	Submersed	0.18	181	148
	Emerge/Float	0.07	161	149
	Sensitive	0.16	251	210

Table C.3: Optimal GLMs for between lake analyses to evaluate effects of shoreline development on macrophyte richness metrics for all lakes. Response variables included total, submersed, emergent/floating, and sensitive species richness. Model development for each of the response variables followed a backwards stepwise selection approach that began with all explanatory variables and their second-order interactions.

	Total	Submersed	Emergent/floating	Sensitive
(Intercept)	2.63^{***}	-0.54^{***}	-1.13^{***}	0.13
	(0.24)	(0.10)	(0.29)	(0.49)
Area	0.30^{***}	0.05^{***}	$-0.10^{\cdot}$	-0.15^{**}
	(0.05)	(0.01)	(0.05)	(0.06)
Depth	-0.02	0.02	0.11	-0.77^{***}
	(0.07)	(0.02)	(0.09)	(0.21)
TSI	-0.02^{***}	-0.01^{***}	0.00	-0.03^{***}
	(0.00)	(0.00)	(0.01)	(0.01)
Dock	0.04	0.11^{***}	-0.05^{***}	0.46^{*}
	(0.05)	(0.03)	(0.01)	(0.23)
PC1	-0.57^{***}	0.02	0.17^{**}	0.19
	(0.04)	(0.03)	(0.06)	(0.14)
Area:Depth	-0.03^{***}			0.07^{**}
	(0.01)			(0.02)
Area:TSI	0.00^{*}		0.00	
	(0.00)		(0.00)	
Area:Dock	-0.03^{***}	$-0.01^{\cdot}$		
	(0.01)	(0.01)		
Area:PC1	-0.01			-0.03
	(0.01)			(0.02)
Depth:TSI	0.01^{***}		$0.00^{\cdot}$	0.01^{*}
	(0.00)		(0.00)	(0.00)
TSI:Dock	0.00^{**}			-0.01^{*}
	(0.00)			(0.00)
TSI:PC1	0.01^{***}		0.00^{*}	0.01^{***}
	(0.00)		(0.00)	(0.00)
Dock:PC1	0.05^{***}		0.03^{**}	-0.11^{***}
	(0.01)		(0.01)	(0.02)
Depth:PC1		-0.04^{***}		
		(0.01)		
Depth:Dock				-0.11^{**}
				(0.04)
AIC	10997.51	6698.26	5932.69	4676.45
BIC	11071.36	6740.46	5985.44	4745.02
Log Likelihood	-5484.75	-3341.13	-2956.34	-2325.22
Deviance	4169.67	976.54	810.50	1536.43
Num. obs.	1444	1444	1444	1444

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Table C.4: Optimal GLMs for between lake analyses to evaluate effects of shoreline development on macrophyte richness metrics for shallow lakes with low watershed development. Response variables included total, submersed, emergent/floating, and sensitive species richness. Model development for each of the response variables followed a backwards stepwise selection approach that began with all explanatory variables and their second-order interactions.

	Total	Submersed	Emergent/floating	Sensitive
(Intercept)	2.36^{***}	-0.79^{***}	-1.00^{***}	-2.08^{**}
	(0.05)	(0.13)	(0.02)	(0.78)
Area	0.16^{***}	0.07^{***}		$0.35^{\cdot}$
	(0.01)	(0.02)		(0.19)
Dock	0.28^{***}	0.16^{*}	-0.06^{**}	-0.26^{***}
	(0.05)	(0.08)	(0.02)	(0.03)
Area:Dock	-0.04^{***}	-0.02		
	(0.01)	(0.02)		
TSI		-0.01^{**}		0.02
		(0.00)		(0.02)
Area:TSI				-0.01^{*}
				(0.00)
AIC	3255.56	2073.29	1874.34	1889.48
BIC	3271.90	2093.71	1882.51	1909.91
Log Likelihood	-1623.78	-1031.65	-935.17	-939.74
Deviance	1122.96	317.78	205.82	591.28
Num. obs.	439	439	439	439

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Table C.5: Optimal GLMs for between lake analyses to evaluate effects of shoreline development on macrophyte richness metrics for deep lakes with low watershed development. Response variables included total, submersed, emergent/floating, and sensitive species richness. Model development for each of the response variables followed a backwards stepwise selection approach that began with all explanatory variables and their second-order interactions.

	Total	Submersed	Emergent/floating	Sensitive
(Intercept)	2.07^{***}	-0.52^{***}	-1.05^{***}	-1.75^{***}
	(0.14)	(0.10)	(0.03)	(0.10)
Area	0.13^{***}			0.03
	(0.01)			(0.02)
TSI	0.01^{***}	-0.01^{**}		
	(0.00)	(0.00)		
Dock	0.36^{***}	0.09^{***}	-0.05^{**}	-0.33^{***}
	(0.08)	(0.01)	(0.02)	(0.03)
Area:Dock	-0.03^{***}			
	(0.01)			
TSI:Dock	0.00^{*}			
	(0.00)			
AIC	3414.14	2046.16	1814.34	1684.76
BIC	3438.29	2058.24	1822.39	1696.84
Log Likelihood	-1701.07	-1020.08	-905.17	-839.38
Deviance	1313.48	244.83	197.65	529.36
Num. obs.	414	414	414	414

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Table C.6: Optimal GLMs for between lake analyses to evaluate effects of shoreline development on macrophyte richness metrics for shallow lakes with high watershed development. Response variables included total, submersed, emergent/floating, and sensitive species richness. Model development for each of the response variables followed a backwards stepwise selection approach that began with all explanatory variables and their second-order interactions.

	Total	Submersed	Emergent/floating	Sensitive
(Intercept)	2.93^{***}	-0.08	-1.76^{***}	-1.10^{*}
	(0.40)	(0.15)	(0.19)	(0.43)
Area	0.36^{***}			
	(0.09)			
TSI	-0.02^{*}	-0.01^{***}	0.01^{***}	-0.03^{***}
	(0.01)	(0.00)	(0.00)	(0.01)
Dock	0.05^{**}	0.07^{**}	-0.07^{*}	
	(0.02)	(0.02)	(0.03)	
Area:TSI	0.00^{**}			
	(0.00)			
AIC	2685.90	1438.77	1318.01	607.67
BIC	2705.22	1450.36	1329.60	615.40
Log Likelihood	-1337.95	-716.39	-656.01	-301.84
Deviance	1218.87	264.95	278.05	312.09
Num. obs.	352	352	352	352

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Table C.7: Optimal GLMs for between lake analyses to evaluate effects of shoreline development on macrophyte richness metrics for deep lakes with high watershed development. Response variables included total, submersed, emergent/floating, and sensitive species richness. Model development for each of the response variables followed a backwards stepwise selection approach that began with all explanatory variables and their second-order interactions.

	Total	Submersed	Emergent/floating	Sensitive
(Intercept)	4.55^{***}	0.11	-1.11^{***}	-0.71
	(0.40)	(0.33)	(0.06)	(0.44)
Area	-0.20^{*}	0.05^{*}		0.14^{*}
	(0.08)	(0.02)		(0.06)
TSI	-0.04^{***}	-0.02^{**}		-0.05^{***}
	(0.01)	(0.01)		(0.01)
Dock	0.06^{**}	-0.20	-0.11^{***}	-0.18^{*}
	(0.02)	(0.15)	(0.03)	(0.09)
Area:TSI	0.00^{**}			
	(0.00)			
TSI:Dock		0.00		
		(0.00)		
AIC	1904.47	1155.20	943.91	603.07
BIC	1921.86	1172.58	950.86	616.97
Log Likelihood	-947.24	-572.60	-469.96	-297.53
Deviance	764.93	148.14	148.89	210.26
Num. obs.	239	239	239	239

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Table C.8: Performance statistics for optimal GLMMs that evaluated potential within-lake effects of docks. Psuedo-R^2 describes the R^2 value of the regression of observed response values against the fitted values for each optimal model. Intercept and slope describe the parameters of each regression model used to obtain pseudo-R^2.

Response	Pseudo-R^2	Intercept	Slope
Total	0.24	0.21	0.92
Submersed	0.90	-0.64	1.27
Sensitive	0.42	-0.01	1.03

Table C.9: Results of model comparisons to determine structure of fixed effects in GLMMs that evaluated within-lake effects of docks (fig. 3.2). Response variables were total and submersed species richness and sensitive species presence/absence. Fixed effects evaluated were distance to nearest dock (Distance), main effects of distance to nearest dock and depth of point (Distance + Depth), and second-order interactions between variables (Distance:Depth, including main effects). Probability (p) values indicate the significance of analysis of variance results comparing the three nested models for each response variable.

Response	Fixed effects	AIC	$\log(Lik)$	p
Total	Distance	1544.9	-769.5	
Total	Distance + Depth	1190.0	-591.0	<0.005
Total	Distance:Depth	1187.8	-588.9	0.040
Submersed	Distance	294.7	-144.4	
Submersed	Distance + Depth	295.2	-143.6	ns[a]
Submersed	Distance:Depth	296.4	-143.2	ns
Sensitive	Distance	930.9	-462.5	
Sensitive	Distance + Depth	932.9	-462.5	ns
Sensitive	Distance:Depth	876.0	-433.0	<0.005

[a]ns, not significant at $\alpha = 0.05$

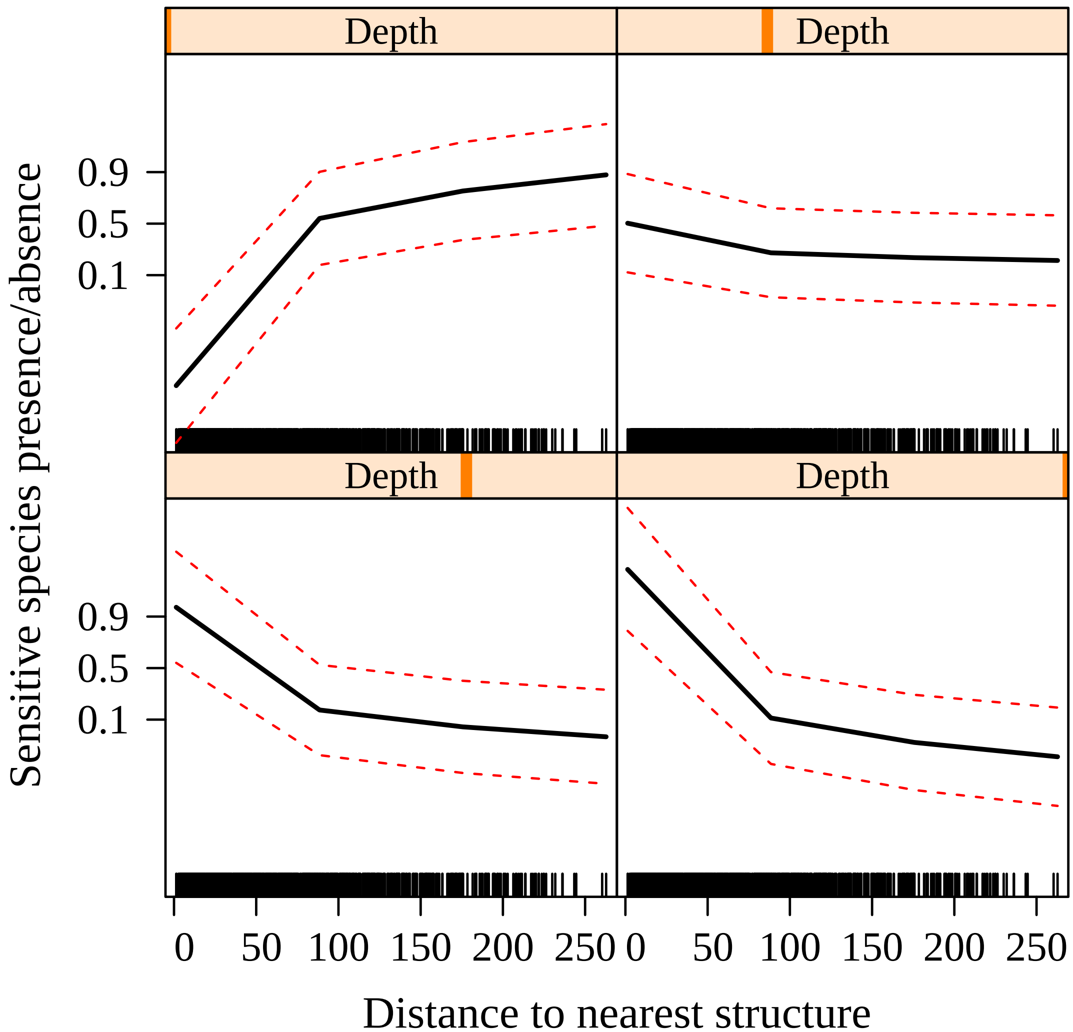


Figure C.1: Effects plots indicating the interactive effects of distance to nearest structure (m) and depth (m) on sensitive species presence/absence (indicated by log-odds) for within-lake analyses. The rug-plot at the bottom of each figure indicates the marginal distribution of distance to nearest structure. Vertical orange bars indicate the value at which depth at each point was held constant to evaluate the effect of distance to nearest structure, such that point depth increases from top-left to bottom-right. Dashed lines indicate 95% confidence intervals.

Appendix D

Chapter 4 Additional neural network information for lake IBI

Table D.1: MLR models using all variables and stepwise selection for all lakes and northern/southern groups. All models were significant at $\alpha = 0.05$.

	All	North	South	All step	North step	South step
(Intercept)	112.38^{***}	$57.55^{\cdot}$	222.80^{***}	114.67^{***}	60.60^{*}	228.41^{***}
	(8.35)	(33.34)	(28.79)	(6.26)	(28.40)	(28.10)
hectares	0.00	0.00	0.00	0.00		
	(0.00)	(0.01)	(0.00)	(0.00)		
depth_m	-0.24^{*}	0.20	0.53	-0.24^{*}		0.60
	(0.11)	(0.35)	(0.42)	(0.11)		(0.37)
tsi	-0.82^{***}	-0.68	-1.20^{***}	-0.81^{***}	$-0.73^{\cdot}$	-1.24^{***}
	(0.10)	(0.48)	(0.20)	(0.09)	(0.38)	(0.19)
GDD	0.00	0.03^{*}	-0.03^{*}		$0.02^{\cdot}$	-0.04^{**}
	(0.00)	(0.01)	(0.01)		(0.01)	(0.01)
ag	-17.41^{***}	-46.71	-18.97^{*}	-16.79^{***}		-19.29^{*}
	(4.45)	(150.98)	(8.80)	(4.19)		(8.10)
wshed_imperv	-75.42	-65.44	$-69.60^{\cdot}$	-68.08		-66.95^{*}
	(47.39)	(504.20)	(35.72)	(43.85)		(32.47)
wshed_well	$-0.29^{\cdot}$	-1.06	-0.21	$-0.28^{\cdot}$	-0.98	
	(0.16)	(0.70)	(0.17)	(0.16)	(0.63)	
wshed_sa	0.01^{*}	0.00	0.00	0.01^{*}		
	(0.00)	(0.01)	(0.01)	(0.00)		
CPI	-0.27^{**}	-0.31	-0.21	-0.25^{**}		
	(0.09)	(0.26)	(0.23)	(0.08)		
num_sc	-0.36^{*}	-1.75^{**}	$-0.70^{\cdot}$	-0.34^{*}	-1.63^{**}	-0.76^{*}
	(0.15)	(0.56)	(0.36)	(0.14)	(0.48)	(0.34)
R^2	0.74	0.27	0.64	0.74	0.25	0.62
Adj. R^2	0.72	0.16	0.59	0.72	0.20	0.60
Num. obs.	166	72	94	166	72	94

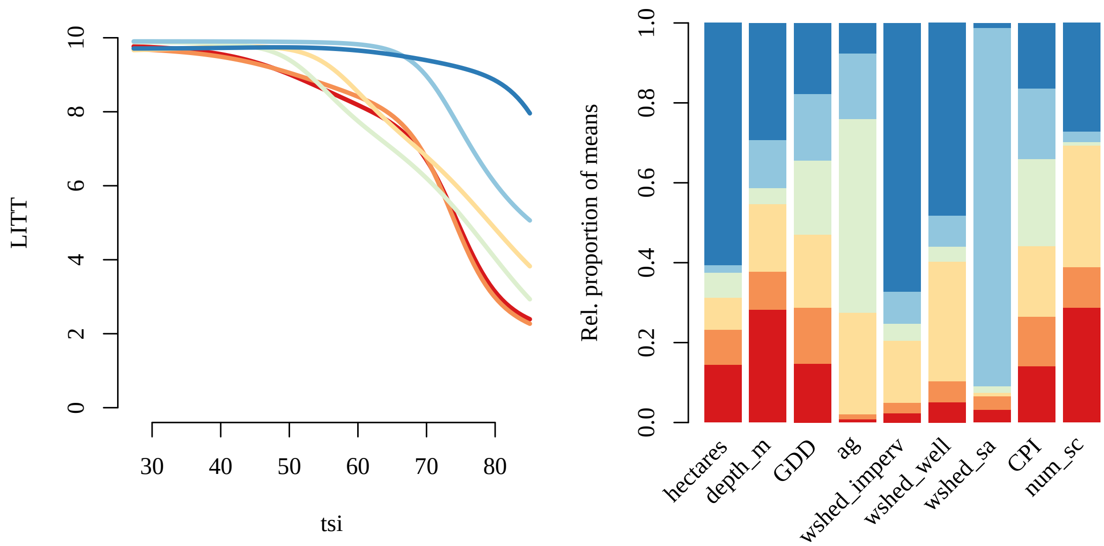
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Table D.2: Summary of GAMs for all lakes and the southern group. Estimated degrees of freedom (edf) describe relative smoothness for each term. Insufficient sample size prevented creation of a model for the northern group.

	All		South	
	edf	F	edf	F
s(hectares)	3.65	5.31***	4.76	2.65*
s(depth_m)	8.22	2.99**	3.25	2.43
s(tsi)	0.96	69.26***	1.00	50.15***
s(GDD)	4.15	3.69**	1.00	10.21**
s(ag)	0.99	6.95**	1.00	4.97*
s(wshed_imperv)	1.66	1.41	1.00	2.85
s(wshed_well)	0.84	0.46	1.00	1.05
s(wshed_sa)	2.78	6.34***	3.78	1.70
s(CPI)	6.10	2.14*	1.06	0.63
s(num_sc)	3.69	2.90*	1.00	6.27*
R^2	0.79		0.68	
Dev. expl.	0.83		0.75	
Num. obs.	166		94	

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

(a)



(b)

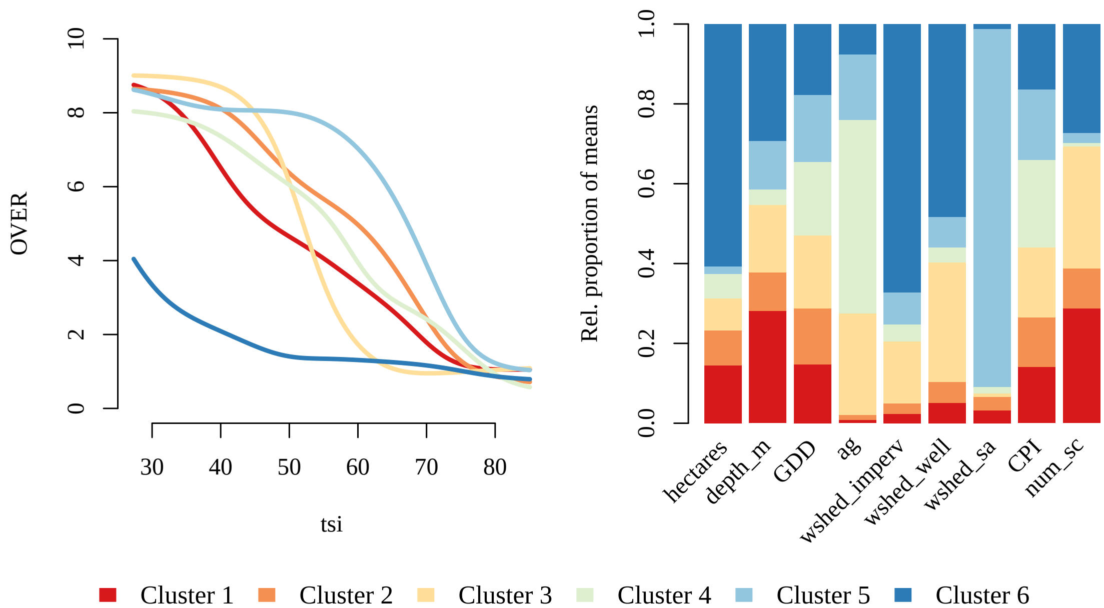
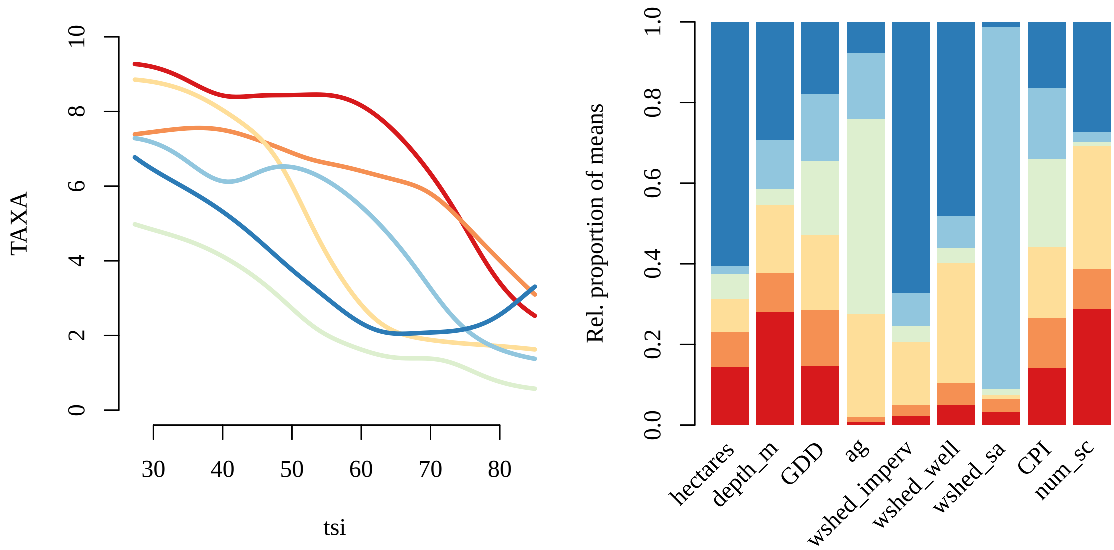


Figure D.1: Response of LITT and OVER metrics to explanatory variables indicated by neural networks for all lakes (see table 4.3). Subfigure (a) shows LITT response to lake trophic state (*tsi*) and (b) shows OVER response to lake trophic state (*tsi*). Metric response is specific to lake clusters identified using an agglomerative clustering technique. All other explanatory variables were held constant at the mean values for each lake cluster. The bar plots indicate approximate mean value for each explanatory variable relative to all lake clusters.

(a) All lakes



(b) Northern lakes

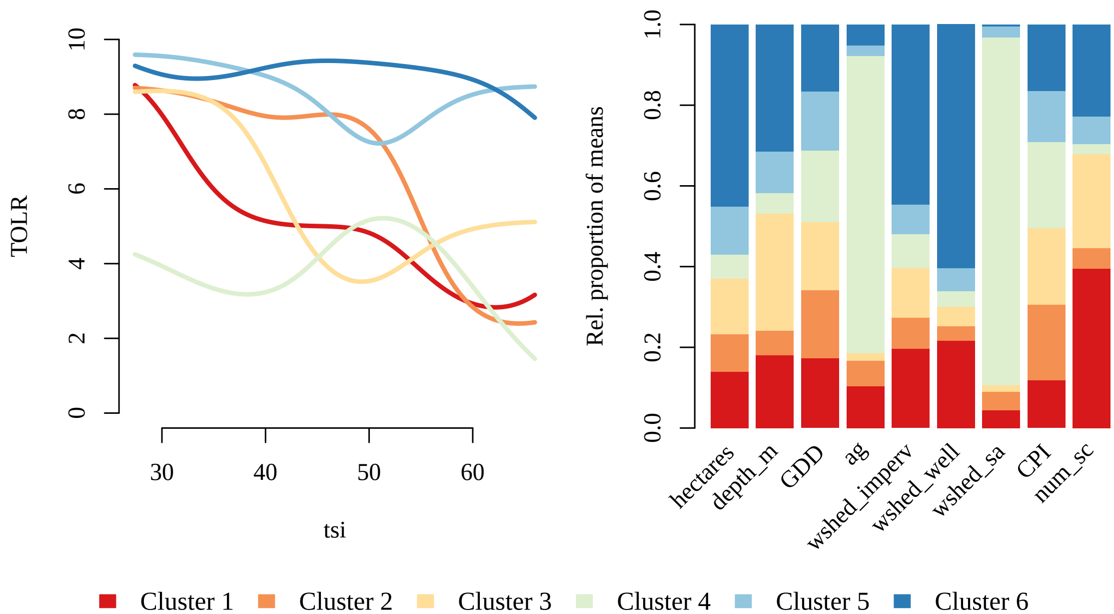


Figure D.2: Response of TAXA and TOLR metrics to lake trophic state (*tsi*) indicated by neural networks (see table 4.3). Subfigure (a) shows TAXA response to lake trophic state (*tsi*) for all lakes and (b) shows TOLR response to lake trophic state (*tsi*) for northern lakes. Metric response is specific to lake clusters identified using an agglomerative clustering technique. All other explanatory variables were held constant at the mean values for each lake cluster. The bar plots indicate approximate mean value for each explanatory variable relative to all lake clusters.

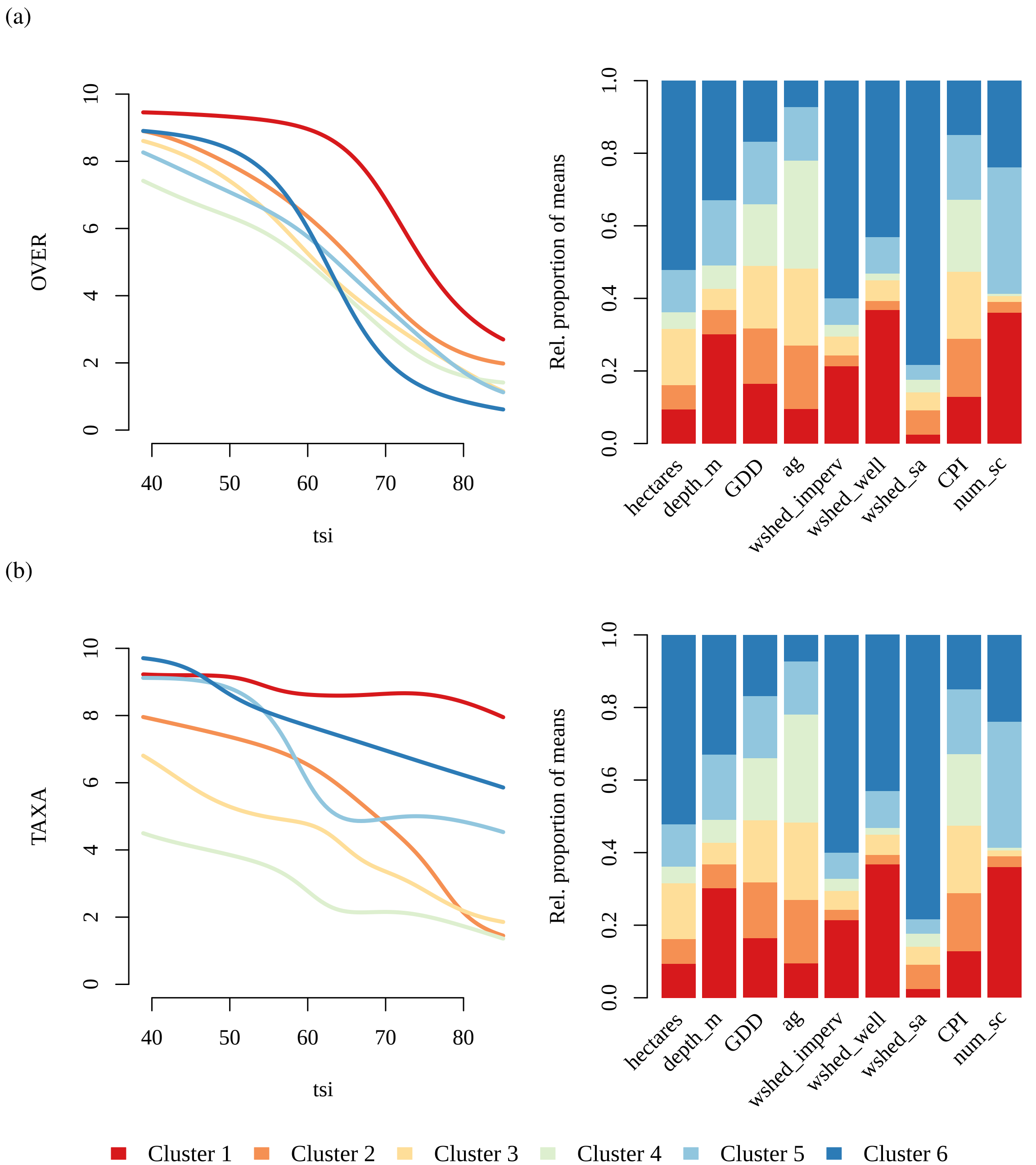


Figure D.3: Response of OVER and TAXA metrics to explanatory variables indicated by neural networks for southern lakes (see table 4.3). Subfigure (a) shows OVER response to lake trophic state (*tsi*) and (b) shows TAXA response to lake trophic state (*tsi*). Metric response is specific to lake clusters identified using an agglomerative clustering technique. All other explanatory variables were held constant at the mean values for each lake cluster. The bar plots indicate approximate mean value for each explanatory variable relative to all lake clusters.

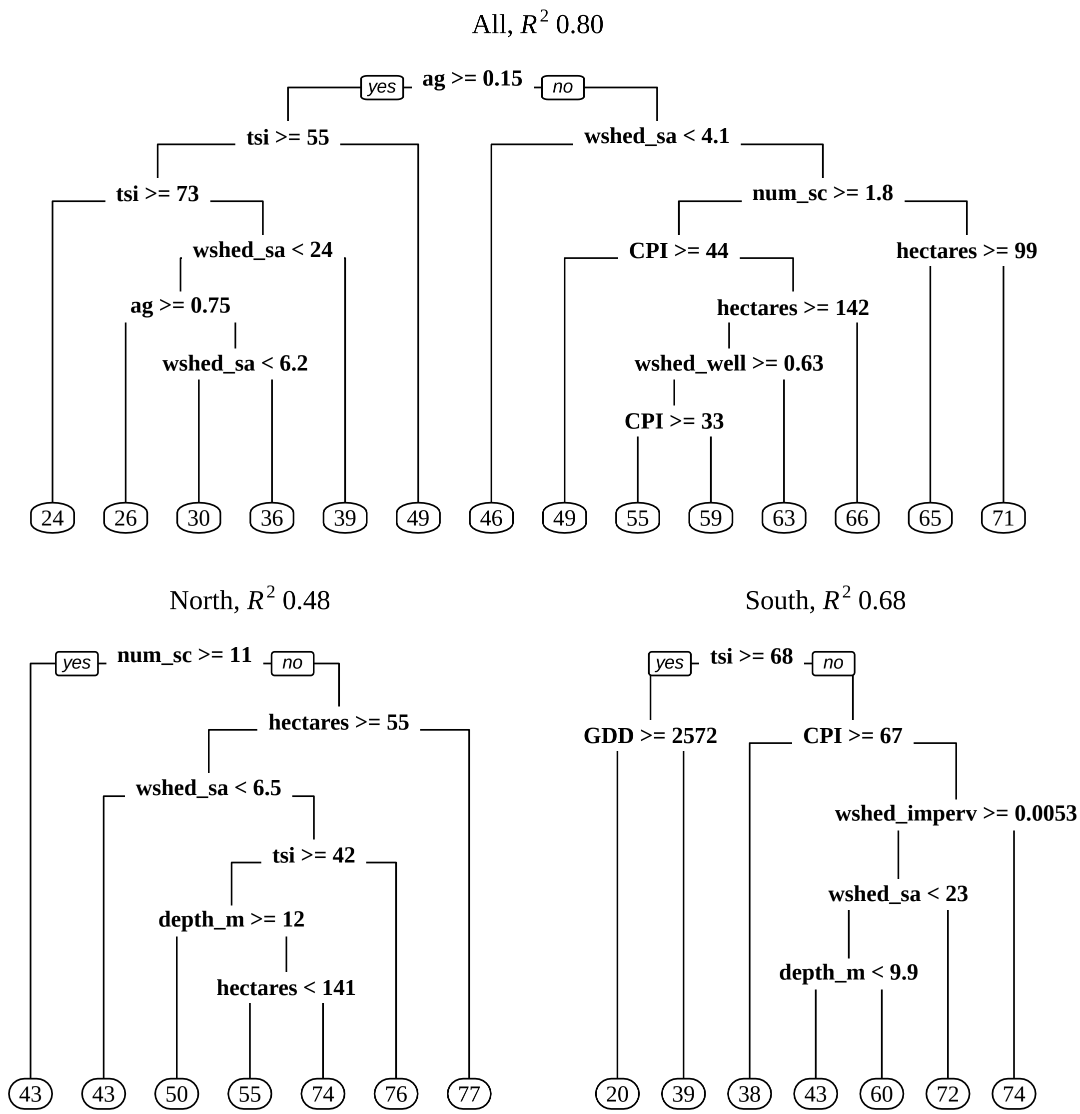


Figure D.4: Regression tree models for all, northern, and southern lake groups. Model fits are based on R^2 values of the linear fit between predicted and observed using the training datasets. All models were created with complexity parameters set as zero. Tree splits based on explanatory variables are identified for each node, with left splits satisfying the condition in the node title. Mean IBI scores for each terminal node are indicated at the bottom of each tree.

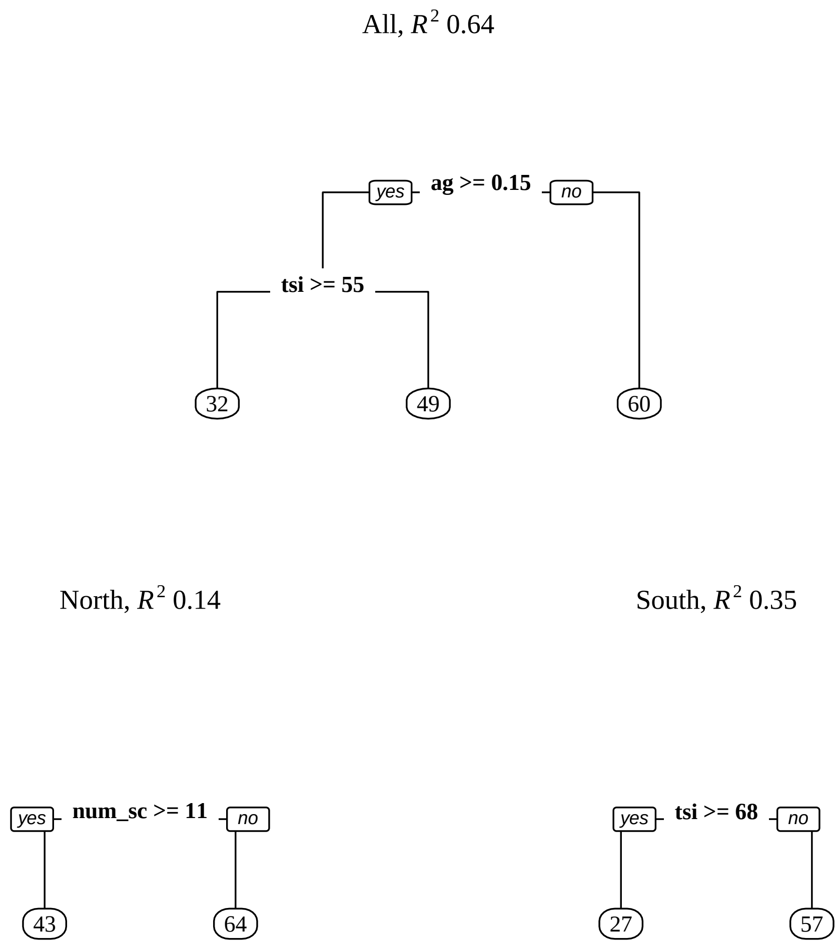


Figure D.5: Regression tree models for all, northern, and southern lake groups. Model fits are based on R^2 values of the linear fit between predicted and observed using the training datasets. All models were created using optimal complexity parameters. Tree splits based on explanatory variables are identified for each node, with left splits satisfying the condition in the node title. Mean IBI scores for each terminal node are indicated at the bottom of each tree.

Appendix E

Chapter 4 Additional neural network information for stream IBI

Summary of analyses

The neural network approach used to model lake IBI performance in chapter 4 was evaluated using stream IBI scores for a large dataset (Niemela and Feist, 2000, 2002). Sample size was over 1000 stream reaches as compared to 332 using lake IBI scores. The analysis was conducted to determine if neural network performance could be improved using a large dataset. The lake and stream IBIs are not ecologically comparable.

The neural network evaluated 1173 sites after parsing the data (over 3000 sites) based on stream thermal regime and missing values for covariates. Only warmwater sites were evaluated. Additionally, neural network models were developed using IBI scores as the response variable because metrics and metric scoring vary for sites depending on drainage area, basin (HUC 04), ecoregion, and thermal regime. Stream temperature was considered the most influential covariate for IBI scores and was used to select the sites (i.e., coldwater removed). Other stream characteristics affect IBI scores but different metric scaling allowed for approximate comparability among sites with natural variability in fish community composition.

Approximately 50 explanatory variables were included in the database for stream IBIs. Ten variables were retained for analysis using VIF to reduce collinearity and selection based on best professional judgment. Remaining variables included phosphorus (*Phos*), total suspended solids (*TSS*), water temperature (*TempH2O*), drainage area (*DrainSqMi*), percent habitat as pool (*PctPool*), percent habitat as fine substrate (*PctFines*), percent habitat as embedded (*PctEmbed*), percent habitat as undercut banks (*PctUnderCut*), percent habitat as woody substrate (*PctWoody*), and percent land use as undisturbed in a 30 meter riparian buffer (*PctUnDistLU30*).

Neural network development and evaluation proceeded using identical methods in sections 4.2.2 and 4.2.3. NMSE values for the training, validation, and test datasets were 0.489, 0.738, and 0.812, respectively. Indications of variable importance following bootstrap analyses were insignificant with all confidence intervals containing zero (fig. E.2). Overall, the ability of neural networks to characterize IBI performance in streams was similar to lake models. Increased sample size of the stream IBI dataset did not greatly improve the ability of neural networks to quantify IBI performance.

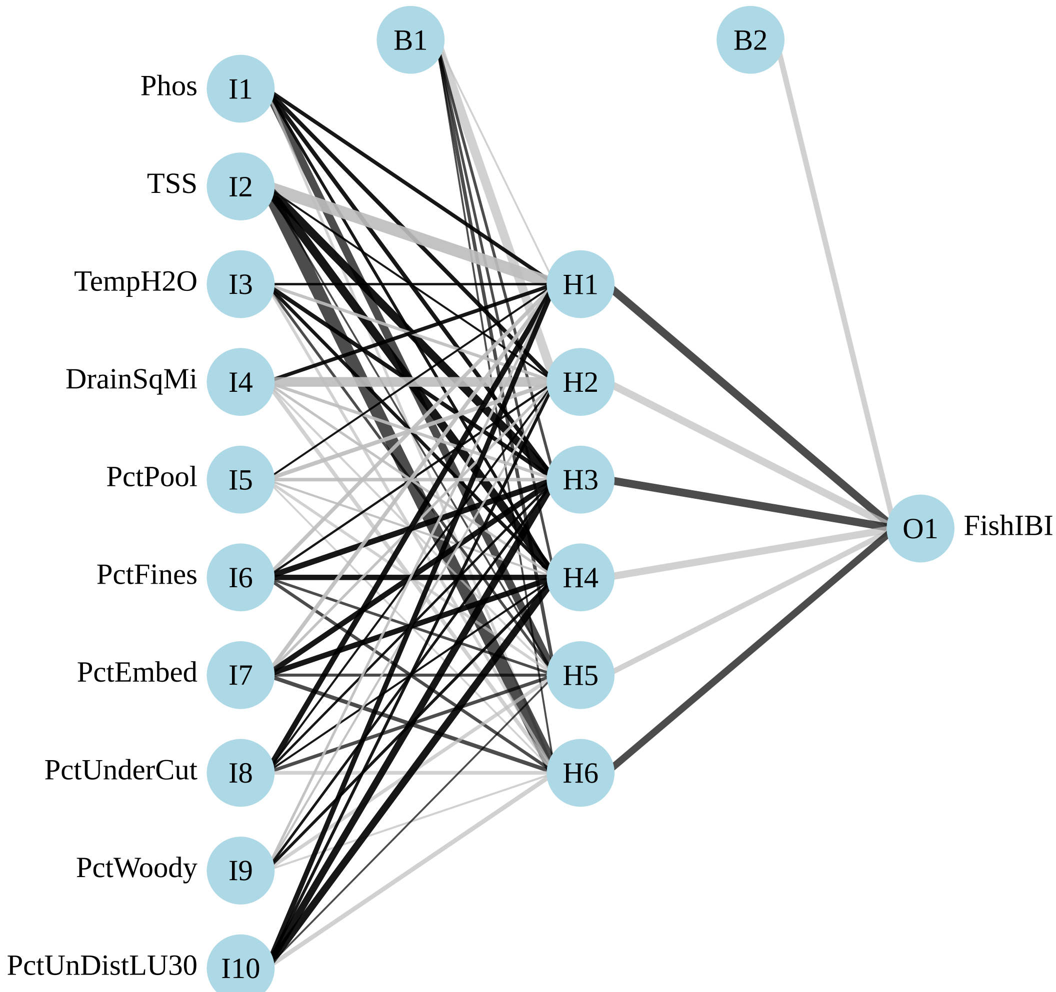


Figure E.1: Optimal neural network model for stream IBI scores that minimized prediction error on the validation dataset. Parameters were decay 0.003, six hidden nodes, and 2352 for the random seed that generated the starting weights. Connections between layers are colored by sign (positive black, negative grey) and have width in proportion to relative weights (Özesmi and Özesmi, 1999).

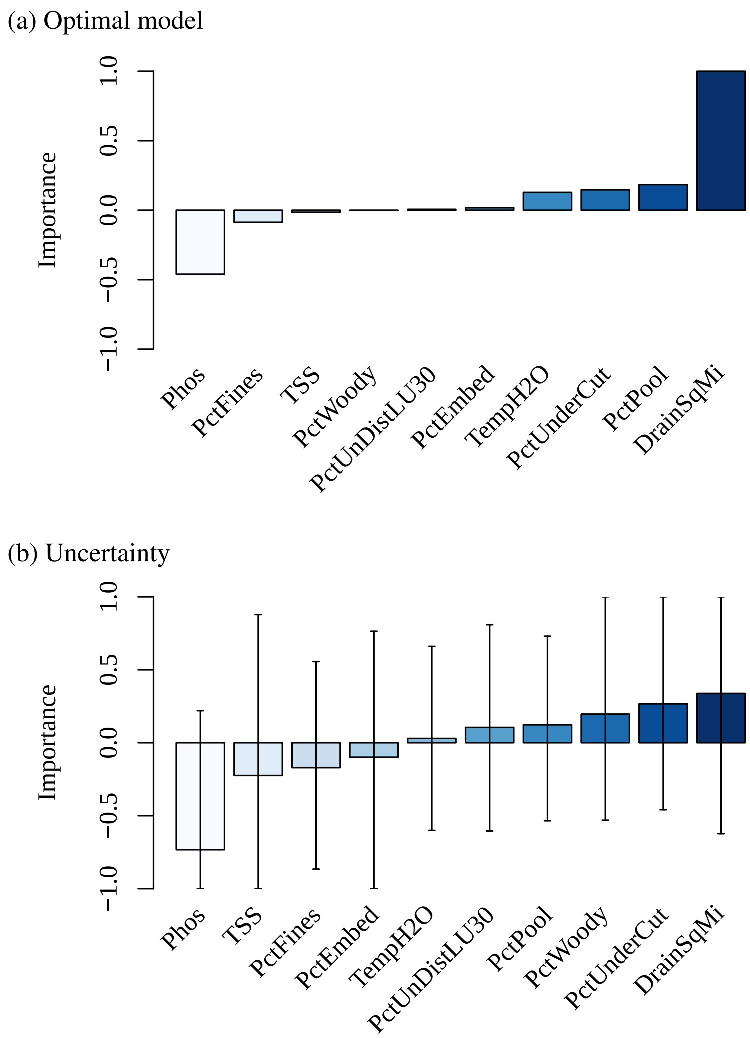


Figure E.2: Relative importance (Garson, 1991; Goh, 1995) values of explanatory variables used in the neural network for stream IBI scores. Subfigure (a) illustrates relative importance values for the optimal model and (b) illustrates uncertainty associated with relative importance using mean, 2.5^{th}, and 97.5^{th} percentile values from bootstrap analyses.